The Internationalization of Firms:

Cross-border Investments, Cultural Diversity and Firm Performance

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von

Michaela Susanne Trax

aus

Ebersberg

Referent:	Prof. Dr. Südekum
Korreferent:	Prof. Dr. Paul
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Chapter 1

Introduction

Analyzing the causes and consequences of international trade, the traditional international trade literature used to focus on country or industry comparative advantages, increasing returns to scale in the production process, and consumer love of variety, but paid little attention to the unit of observation that actually drives the observed trade flows: firms.

However, in the past fifteen years, with increasing availability of detailed micro datasets, the focus shifted to the firm level. A very active research strand documents that despite the gigantic dimensions of international trade and foreign direct investments (FDI) at the aggregate level, the share of firms that are in fact engaged in international activities is surprisingly low. On average, less than five percent of all firms export their products, and even less firms invest abroad. Though these firm types are rare, many studies find them to perform systematically better than purely domestic firms even before their actual foreign market entry (Bernard et al., 2007b). These empirical regularities inspired the development of the so-called "new, new trade models" that stress within-industry heterogeneity of firms (Melitz, 2003; Bernard et al., 2003; Helpman et al., 2004). Together, this research contributed successfully to a better understanding of the selection of certain firms into international activities and of the effects of international trade on economic performance.

In these models, it is usually assumed that all FDI are greenfield investments, that is, firms construct new establishments in the foreign country. However, in particular between highly developed countries, cross-border mergers and acquisitions (M&A) of existing foreign firms are largely responsible for the recent increase of international capital flows. Global FDI growth seems to be strongly driven by merger waves, while greenfield investments appear to be relatively less volatile over time. In years of merger wave peaks, cross-border M&A flows account for up to 80% of global FDI (UNCTAD, 2010).

The results from analyses for greenfield investments and exporting cannot be transfered directly to the case of cross-border M&A as different motives, such as the access to complementary technology or location-specific knowledge, might matter in the decision for this entry mode (Nocke & Yeaple, 2007). The aim of the first three chapters of this thesis thus is to extend the literature on heterogeneous firms and international trade with analyses of cross-border M&A as a specific form of FDI. Based on detailed European firm-level balance sheet information combined with a large global M&A database, the contributions provide empirical evidence on the characteristics of participants in cross-border deals and on the effects of this form of international activity on the investing firms.

However, globalization is not restricted to international trade and FDI. Parallel to these developments, the labor force became more international as well. Migration across national boundaries increased significantly. In the early nineties, 5% of the total population of OECD countries were foreign born according to The World Bank World Development Indicators. The share of migrants rose to 9% in 2010, with large variations across countries. While most of the public and economic discussion is focused on the increasing presence of foreign-born on different labor market outcomes, another important aspect is the composition of migrants. Developed countries, and in particular large cities, attract people from all over the world. As a result, the cultural mix changes in many societies (Ottaviano & Peri, 2006).

Due to their different cultural backgrounds, international migrants bring new knowledge, abilities, and ideas from their country of origin to the domestic economy. In addition to cultural diversity as a consumption amenity, several recent papers could show that the interaction between diverse migrants and native people rises cities' or regions' productivity levels if complementary abilities are combined (Ottaviano & Peri, 2006; Südekum et al., 2012, among others).

In addition to cross-border acquisitions, employing a culturally diverse workforce or a location in a diverse region can also provide firms with access to new, complementary knowledge that might be specific for the migrants' country of origin. The effect of the increase in cultural diversity among foreign workers, and its impact on the performance of plants is the focus of the last chapter of this work. The analysis is again carried out at the micro level of establishments and is combined with data on the composition of the plant and region workforce.

The internationalization of firms and the relation to plant and firm performance is the unifying theme of this doctoral thesis. The four following chapters are individual contributions and are briefly summarized in the following.

Chapter 2, "The effects of cross-border mergers and acquisitions on the acquirers' domestic performance: firm-level evidence", provides empirical evidence on the effects of M&A on the investing firms' domestic performance in the U.K. and France. A new firm-level dataset is built up that combines a global M&A database with balance sheet data for the years 2000 to 2007. Combining matching techniques with a difference-in-differences estimator, cross-border M&A are shown to boost on average acquirers' domestic sales and investment, and cross-border deals do not appear to be accompanied by a downsizing of the domestic labor force in neither of both countries. Further, acquisitions in knowledge-intensive industries lead to improvements in domestic productivity. The results display some heterogeneity across industries and types of acquisitions, suggesting a connection between the motives for international M&As and their resulting effects.

This chapter is based on a cooperation together with Dr. Joel Stiebale, Lecturer of Industrial Economics, Nottingham University Business School. In 2011, this work was published in the Canadian Journal of Economics, volume 44, issue 3, pages 957–990.

Chapter 3, "Productivity and the internationalization of firms: cross-border acquisitions versus greenfield investments", extends the literature on the determinants of international activity at the firm level towards cross-border acquisitions and greenfield investments as different modes of FDI. Using a rich dataset of British firms, multinationals (MNEs) are shown to be characterized by higher productivity levels than exporters on average. However, the productivity ranking predicted by Helpman et al. (2004) does not hold within all types of industries and across all modes of foreign direct investment. In line with Nocke & Yeaple (2007) it matters whether multinational firms engage abroad via greenfield investments or cross-border acquisitions. Cross-border deals involve the most productive firms in sectors with a high share of intangible assets, but the least productive group of all internationally active firms in other industries.

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Chapter 4, "Who buys who in international trade" makes use of a newly constructed dataset that combines information on both European acquirer and target firms in domestic and cross-border M&A deals with a large group of control firms that are not involved in any acquisition activity. The direct link between the two sides of acquisitions contributes to two research questions. First, the complete productivity ranking of acquirer, target, and domestic firms can be described. In contrast to previous work, the self-selection mechanism of firms into international acquisitions and the cherry-picking of suitable target firms are analyzed simultaneously and for a cross-country dataset. Second, the M&A literature on "who buys who" is extended towards cross-border acquisitions. The distribution of the performance advantage of acquiring firms in direct comparison to their chosen targets in the foreign country is analyzed. Systematic differences in the results show up for domestic and cross-border deals.

This third chapter is again single authored. The M&A and firm data used for the three research projects on cross-border mergers and acquisitions was kindly provided by the Rheinisch-Westfälisches Institut für Wirtschaftsforschung in Essen.

Chapter 5, titled “Cultural diversity and plant productivity”, turns to the analysis of the effects of an internationalized labor force. It extends the literature on the effects of cultural diversity on the economic performance as it analyzes two channels through which a culturally diverse workforce can have an impact on the productivity at the establishment level. The composition of the plants’ own workforce, where native and non-native workers from different nations interact directly, influences plant efficiency, but the diversification of the regional workforce at the plants’ location can also generate knowledge spillovers. Complementarities in skills and problem-solving abilities stemming from different cultural backgrounds might improve the plants’ measured performance, while higher transaction costs due to communication problems probably decrease plant efficiency. Production functions augmented with detailed plant and region workforce information are estimated for a comprehensive sample of German establishments. Potential endogeneity problems are addressed in a System GMM framework. We find positive impacts of a culturally diverse region workforce in particular for small, technology-intensive plants, and in the service sector. The diversity of the own workforce additionally increases the productivity of large, manufacturing plants.

This chapter is based on joint work together with Dr. Jens Südekum, Professor of Economics, University of Duisburg-Essen, and Dr. Stephan Brunow, Researcher at the Institute for Employment Research (IAB) in Nürnberg. The data was kindly provided by the Research Data Center (FDZ) of the Federal Employment Agency. This research is an outcome of the research project “Migrant diversity and regional disparities” that is part of NORFACE, a European Research Program on migration.

Chapter 2

The effects of cross-border mergers and acquisitions on the acquirers' domestic performance: firm-level evidence

2.1 Introduction

Increasing values of foreign direct investment (FDI) flows still cause heated debates in most developed countries. Cross-border mergers and acquisitions (M&As) constitute nowadays a major share of transnational investment after having increased sharply in the last two decades. In years of merger waves, cross-border M&A flows amounted up to 80% of global FDI and the total value of worldwide cross-border M&As amounted to over one trillion US dollar in 2007.[1] Advocates point out productivity improvements in firms that decide to 'go global'. These could either stem from cost differences between countries or from access to new technologies helping firms to stay competitive. Opponents, in contrast, fear both the replacement of jobs if firms decide to relocate production abroad, and the loss in bargaining power of workers and sequent wage reductions due to the thread of investing abroad.

Cross-border M&As as a form of FDI started to receive more and more attention in the international trade literature only recently (see, for example, Nocke & Yeaple, 2007, 2008; Neary, 2007; Head & Ries, 2003). Empirical evidence on the effects of cross-border M&As is still sparse and mostly limited to the analysis of the impact on target firms, whereas there is no empirical work explicitly dealing with the effects on the investing enterprises.[2]

Analyzing the consequences of cross-border M&As on the investing firms is important both from a theoretical as well as from an economic policy point of view. First, recent theoretical contributions stress the importance of heterogeneity in firm characteristics and the role of the different motives behind the choice of a particular foreign market entry mode (Nocke & Yeaple, 2007; Norbäck & Persson, 2007). In these models M&As are predominantly driven by the acquisition of complementary assets and technologies, while greenfield investments do not provide direct access to the foreign stock of knowledge and are rather undertaken to exploit existing firm-specific assets or cross-country differences in production costs. Hence, it is not possible to derive conclusions about the effects of cross-border M&As from studies of aggregate FDI. Second, the few empirical M&A studies that compare the

[1] http://stats.unctad.org/FDI/TableViewer/tableView.aspx?ReportId=901 (accessed September 30, 2010)

[2] E.g. Girma & Görg (2004) and Bandick & Görg (2010) analyze the effects on survival and employment in foreign acquisitions targets, and Benfratello & Sembenelli (2006); Harris & Robinson (2003) look at productivity spillovers in target firms. Breinlich (2008) is one study that considers both sides of a deal comparing characteristics of acquirers and target firms, however he does not address the *effects* on the involved firms.

determinants of international and domestic deals find that motives for cross-border M&As are quite different from those of national deals (Shimizu et al., 2004), which impedes the generalization of results found in the M&A literature.

From an economic policy point of view the research question is important as policy makers may hope for potential productivity gains and a strengthening of the national firms' market position after a deal, but at the same time fear a loss of production due to rationalization and relocation. In the case of cross-border acquisitions, analysis of the combined entity are not sufficient to evaluate a deal, however, as it matters from the policy maker's perspective whether rationalization measures and improvements in efficiency take place at the target or at the acquiring firm, and thus acquisitions increase or reduce output and input demand in the domestic or the foreign country. Moreover, most governments are quite skeptical when it comes to foreign investors buying domestic firms, and in particular, when it comes to industries considered as key to the countries' technological basis. From a global welfare perspective, the net effects of mutual restrictions on cross-border acquisitions depend on the effects both on the acquirer and target firms involved in a deal. An analysis of the acquirer side thus complements the existing knowledge of the effects at the target side of cross-border acquisitions.

To the best of our knowledge, there is no empirical investigation that explicitly deals with the home country effects of cross-border acquisitions at the firm-level. This work fills this gap and aims to identify the effects of cross-border M&As on the domestic growth and productivity of the investing firm.

To provide first evidence on the effects of cross-border M&As on the acquirers' domestic activity, we construct a unique firm-level data set that combines financial data of firms from the United Kingdom (U.K.) and France with a global M&A database for the years 2000-2007. Both the U.K. and France are among the top five countries with respect to cross-border acquisitions worldwide, thus providing enough observations for a detailed analysis. We implement matching techniques in combination with a difference-in-differences estimator to control for selection based on observable characteristics as well as for time-invariant unobserved firm heterogeneity. We find that cross-border deals boost domestic sales growth on average, and they are not accompanied by a downsizing of the domestic labor force in neither of the two countries. Further, there is some evidence that cross-border M&As increase domestic efficiency for acquirers in industries with a high technological intensity.

Although changes in domestic investment, sales, and employment growth vary somewhat across industries, countries, and types of acquisitions, in no case cross-border M&As are associated with significant reductions in domestic economic activity. Apparently, the substitution of activity at home by cheaper production abroad does not appear to be the main motive for cross-border M&As. Those deals seem to either serve foreign market entry or – in particular in technology-intensive industries – to be motivated by the possibility to access the technology and knowledge stock of the foreign target firm.

The rest of this chapter is organized as follows. In the next section, previous research on M&As and FDI is discussed, section 2.3 describes our estimation strategy and section 2.4 provides a description of the data. Results of the empirical analysis are presented in section 2.5 with some robustness checks in chapter 2.6; section 2.7 concludes this chapter.

2.2 Related Literature

Several strands of literature are relevant for the effects of cross-border M&As on the investing firm. We first look at the M&A literature that is usually focused on domestic acquisitions. There is evidence, however, that cross-border acquisitions differ considerably from national acquisitions. Therefore, we try to extract additional predictions from the FDI literature – although much of this literature does not consider the particular mode of foreign market entry. Overall, theoretical predictions regarding the effects on domestic output and input demands as well as efficiency gains after M&As depend crucially on the underlying motives that determine the investment (see Shimizu et al., 2004).

Within the industrial organization literature, the main motives for M&As are the strengthening of market power (Kamien & Zang, 1990) and the realization of efficiency gains. Efficiency gains might stem from technology transfer within the merged entity (Röller et al., 2001), the reallocation of production and technology to more efficient uses (Jovanovic & Rousseau, 2008), or the exploitation of complementary assets in acquirer and target firm (Jovanovic & Braguinsky, 2004). While M&As that are conducted for purely strategic reasons will probably lead to a reduced output level in the merged entity due to rival firms' business expansion, the realization of efficiency gains might have an effect in the opposite direction.

Yet, there are other motives for M&As related to the discussion on unprofitable M&As that do not necessarily imply efficiency increases (Budzinski & Kretschmer, 2009). If M&As arise out of managers' utility maximization, which may include preferences for expansion (an 'Empire-building' motive, see Shleifer & Vishny, 1988), efficiency does not necessarily improve after the deal. Similarly, Jensen (1986) points out that managers have a preference to reinvest free cash rather than to return it to investors.

While several empirical studies find productivity effects of M&As on the combined entity (see, e.g., Conyon et al., 2002b; Maksimovic & Phillips, 2001), this does not necessarily reflect efficiency gains in the acquiring firm, especially in diversifying acquisitions (compare Schoar, 2002).

Supposing that M&As indeed result in an improved efficiency level, a crucial point for policy makers is the source of these improvements. Policy makers and trade unions often argue that efficiency gains are the result of rationalization, especially of downsizing the workforce. Shleifer & Summers (1998) argue that M&As provide an opportunity to cancel implicit contracts with trade unions or employees. Empirical evidence regarding the employment consequences of M&As is mixed. Harris et al. (2005) report that productivity increases after ownership changes are at least partly due to a layoff of workers, disinvestment and outsourcing of production stages. Gugler & Yurtoglu (2004) find that on average M&As within Europe do involve a downsizing of the labor force in the merged firm, while this is not the case for U.S. deals. They trace the difference back to more rigid labor markets in Europe.[3]

The discussion of the related literature so far has neglected the international dimension of M&As. Yet, the characteristics of cross-border deals are quite different from those of national deals. Cross-border M&As are on average much larger than national deals and more often target listed firms (Grimpe & Hussinger, 2008). They are also associated with higher uncertainty, higher risk of failure (Bertrand & Zuniga, 2006; Harris & Ravenscraft, 1991), and with higher (transaction) costs due to the larger cultural distance and institutional differences (Di Giovanni, 2005).

[3]These cross-country differences show up in further studies. Conyon et al. (2002a) find that after an M&A, employment shrinks in the combined firm, and Amess et al. (2008) report negative employment adjustment at the acquired firm using a sample of U.K. targets. In contrast, McGuckin & Nguyen (2001), among others, find that acquired plants in the U.S. are characterized by faster employment growth after the acquisition than other plants.

Therefore, acquirers may require a higher expected return from cross-border acquisitions than from domestic deals. Finally, Frey & Hussinger (2006) find that technological relatedness (in terms of the patent portfolio) of acquirer and target is a significant determinant of cross-border acquisitions, but not of domestic ones.

Cross-border acquisitions are a mode of FDI and might be motivated by the desire to enter foreign markets, by differences in production costs across countries, or the access to country-specific assets in addition to strategic motives.[4] In most theoretical trade models incorporating firm heterogeneity, market access is the most important motive for FDI (Helpman et al., 2004, for instance). This type of market-seeking FDI is usually referred to as horizontal investment. On the one hand, horizontal FDI might reduce domestic production if it comes along with a substitution of exports. If substitution of exporting activities indeed takes place after horizontal cross-border M&As, efficiency in the home country could be negatively affected, as the firm loses economies of scale. On the other hand, FDI might spur headquarter activities such as marketing and R&D as these investments can be applied to a larger production output after a foreign expansion (Fors & Svensson, 2002), which might in turn increase growth in the acquirers' home activity.

There is also scope for vertical investment activity in analogy to Head & Ries (2003), motivated by differences in factor costs across countries. The affiliate, typically located in regions with lower labor costs, then performs part of the firm's production process at a lower cost, i.e. there is offshoring within the firm. While offshoring may involve a substitution between domestic and foreign production, this might be more than offset by a productivity increase that stems from cost savings. Along these lines, Grossman & Rossi-Hansberg (2008) argue that productivity improvements from offshoring can lead to increased demand for the remaining domestic workers. Indeed, existing empirical evidence indicates that offshoring can boost domestic productivity (see, for instance, Amiti & Wei, 2009; Görg et al., 2008), while it is not necessarily associated with declining employment (Crinó, 2009; Amiti & Wei, 2005, 2006).

While the FDI literature provides some guidance to relevant motives for and effects of cross-border investments, the motives for cross-border M&As might be quite different from other types of FDI. In contrast to exporting and greenfield in-

[4]See Helpman (2006) for an overview on the theoretical literature on firms and FDI choices.

vestment, cross-border M&As provide access to existing products that are suitable to and proven and tested in the foreign market. In addition, access to existing networks with customers and suppliers is provided (see Görg, 2000, e.g.). Theoretical models that differentiate between the mode of foreign market entry usually argue that FDI motivated by production cost differences rather takes the form of greenfield investments, while cross-border M&As are primarily conducted to gain access to complementary firm-specific assets in target firms (Nocke & Yeaple, 2008), firm-specific capabilities that are non-mobile across borders and markets (Nocke & Yeaple, 2007), or country specific assets (Norbäck & Persson, 2007). Indeed, empirical evidence suggests that cross-border M&As are rarely associated with input-output linkages (Hijzen et al., 2008). Hence, market access and the exploitation of complementarities are probably more important for cross-border M&As than differences in the costs of production factors. In case of technology-driven cross-border M&As, the acquirer's productivity can be expected to rise due to the acquired complementary knowledge.

Nevertheless, cross-border acquisitions might also be motivated by purely strategic reasons (see, for instance, Horn & Persson, 2001; Neary, 2007). Efficiency differences between firms might be more pronounced across than within countries. These can induce firms to engage in cross-border M&As (see, e.g., Bjorvatn, 2004; Neary, 2007; Bertrand & Zitouna, 2006). As argued by Neary (2007), these cross-border acquisitions can lead to a reallocation of production from less efficient foreign target firms to more efficient acquirers. Hence, for M&As induced by efficiency differences between firms across countries, we would expect an increase in production and employment in acquiring firms.

Several empirical contributions analyze the effects of FDI on the productivity of multinational firms and accompanying substitution of domestic investment and labor without taking into account the different modes of foreign entry.[5] The results from these studies are mixed, especially regarding the question of whether FDI is a substitute for or complementary to domestic activity. The differences in the results may partly stem from institutional differences and distinct industry structures across countries and from a mixture of the extensive and the intensive margin

[5]See for example Pfaffermayr (2004), Becker & Mündler (2010), Konings & Murphy (2006), or Becker & Mündler (2008) on employment; Navaretti & Castellani (2004), Jäckle & Wamser (2010) or Damijan et al. (2007) for productivity, Fors & Svensson (2002) for R&D, and Desai et al. (2009) for investment.

of FDI. In addition, neglecting heterogeneity in the composition of FDI makes it impossible to derive the effects of cross-border acquisitions.

Concluding, as the theoretical literature does not predict unambiguous effects, the issue whether cross-border acquirers substitute domestic activity and can realize efficiency gains boils down to an empirical question. The empirical literature, however, either deals with national deals or looks at FDI flows in the aggregate, and the effect of cross-border acquisitions on the acquirers is still an open question. With this chapter, we aim to provide first evidence.

2.3 Estimation

Our empirical strategy aims to identify the causal impact of cross-border M&As on the performance of the acquiring firm. We employ a propensity score matching procedure combined with a difference-in-differences estimator. This empirical strategy is prominent in labor market evaluation studies (see Heckman et al., 1997, as an example) and became popular in the international trade literature, where Wagner (2002), among others, started to address the impact of exporting on productivity and firm size using a similar methodology.[6]

The evaluation of a treatment effect on the treated s periods after treatment at time t comprises a comparison between the actual outcome and the situation had the firm not invested abroad.

$$\tau_{ATT} = E[y^1_{t+s}|X_{t-1}, CB_t = 1] - E[y^0_{t+s}|X_{t-1}, CB_t = 1], \qquad (2.1)$$

where y^1 is the outcome of an acquirer, y^0 the outcome of the acquirer had it not invested abroad, X contains a set of control variables, and CB is a binary indicator of cross-border M&A activity taking the value one if the firm acquires at least one foreign target in the respective year.

As the counterfactual situation $E[y^0_{t+s}|X_{t-1}, CB_t = 1]$ is not observable, the evaluation problem is often framed as a missing data problem. The main task is to construct a consistent estimate for the average outcome of acquirers had they not invested abroad. The average outcome of the non-acquirers does not provide a good estimate of the counterfactual in non-experimental settings as firms select

[6]See Girma & Görg (2007), Greenaway & Kneller (2008), and Yasar & Rejesus (2005) for further applications of the matching estimator to research questions regarding the effects of exporting and FDI.

themselves into the different groups based on characteristics that might also influence the measured outcome. We use matching techniques to construct a comparison group. The goal of the matching procedure is to identify matches of acquirers and non-acquirers that are similar to each other with respect to a range of observable characteristics. The expected outcome of this comparison group provides a valid construction of the counterfactual outcome under the conditional independence assumption. The conditional independence assumption requires the potential outcome to be independent of the treatment assignment given the set of observable control variables that are not influenced by the treatment:

$$y^1, y^0 \quad \perp \quad CB|X. \tag{2.2}$$

That is, we assume that selection into treatment is based on observable characteristics only, i.e. unobservable variables do not influence simultaneously the treatment assignment and the outcome variables. This assumption is not testable, but the inclusion of a wide range of covariates that are suggested by theory helps to justify the validity of the approach (Caliendo & Kopeinig, 2008).

The number of relevant variables to be included is large, hence we take advantage of Rosenbaum & Rubin's (1983) results: if the conditional independence holds conditional on X, it will also be true for the balancing score. We implement a logit estimation and use the predicted probability of a cross-border deal as the balancing propensity score:

$$\hat{P}(CB_t = 1|X_{t-1}) = \Lambda(\hat{\beta} X_{t-1}), \tag{2.3}$$

where Λ is the cumulative logistic probability function. The matrix X_{t-1} contains only pre-deal characteristics from period $t-1$ to avoid reverse causality problems (Caliendo & Kopeinig, 2008). The best match is a firm not active in cross-border M&As with the propensity score that is closest to the acquirer's score.

As our dataset is a panel, we can release the strong assumption of selection on observables by combining the matching technique with a difference-in-differences estimator (Blundell & Costa Dias, 2000). Instead of comparing differences in the levels of the outcome variables between the two groups we focus on log growth rates. This procedure allows the decision to engage in a cross-border acquisition to be based on the expected returns to this investment and on time-invariant unobservables (Heckman et al., 1997). Still, unobserved time-varying factors that influence both treatment and outcome variables as well as differential reactions to common macroeconomic shocks across treatment and control group would lead to inconsistent results.

The difference-in-differences estimator for the effect of cross-border acquisitions can be expressed as follows:

$$\hat{\tau}_{DID} = E[y^1_{t+s} - y^1_{t-1}|X_{t-1}, CB_t = 1] - E[y^0_{t+s} - y^0_{t-1}|X_{t-1}, CB_t = 0], \quad (2.4)$$

which can be operationalized applying regression analysis to the matched data set with log growth rates as the dependent variable and a dummy for cross-border deals:

$$\Delta y_{i,t+s} = \alpha + \beta CB_{it} + \varepsilon_{it}. \quad (2.5)$$

The difference-in-difference estimate $\hat{\tau}_{DID}$ is then given by the estimated coefficient $\hat{\beta}$ in an OLS regression. This representation makes the analysis of heterogeneous effects across industries straightforward testing for equality of the $\hat{\beta}_k$ using the following estimation equation:

$$\begin{aligned} \Delta y_{i,t+s} &= \alpha_1 ind_{i1} + \cdots + \alpha_K ind_{iK} \\ &+ \beta_1 CB_{it} \times ind_{i1} + \cdots + \beta_K CB_{it} \times ind_{iK} + \varepsilon_{it}. \end{aligned} \quad (2.6)$$

with ind_k, $k = 1, \ldots, K$ dummy variables for the K sectors to be considered.

The second assumption for the validity of the matching procedure, the overlap condition, requires for each set of X_{t-1} of all treated and control firms a positive probability to be involved in a cross-border deal as well as a positive probability not to be involved:

$$0 < P(CB_t = 1|X_{t-1}) < 1. \quad (2.7)$$

This guarantees that a suitable match for each acquirer is in principle available and no perfect prediction based on X_{t-1} is possible. This assumption is less critical in the present case, as the share of acquirers in cross-border deals is small and the pool of potential matches is quite extensive. The results presented are based on estimations where the common support condition is imposed, acquirers off common support are not included.[7] Furthermore, one has to decide whether the matching

[7] Only six French and two British firms are off common support (table 2.4).

procedure is carried out with or without replacement. Basically, this choice involves a trade-off between bias and variance. We decide to perform the propensity score matching with replacement, as in the British sample the balancing quality is reduced considerably in the version without replacement. Therefore, we calculate the variance of the matching estimator with a correction for matching estimators with replacement as suggested by Lechner (2001) to account for the repeated use of several matches.[8]

One potential concern with the propensity score estimation is that the decisions of firms in our comparison group might be affected by the acquirers' decision to invest abroad. Our approach is valid only if the stable unit treatment assumption holds, i.e. if there are no significant general equilibrium effects. If acquirers hamper domestic growth of competitors in the comparison group due to strategic interaction, our results might overestimate the effect of cross-border M&As. For this to happen, however, firms would have to be direct competitors in a market, i.e. only if the demand for the acquirers' products directly affects the non-acquirers' market position. The substitutability of products within two-digit industries – which we use in the estimation of the propensity score – is probably limited. This clearly reduces the risk of overestimation. In addition, the problem is probably even less severe in our application as only a small fraction of firms engages in cross-border M&As and hence average interaction effects are probably small as well (Caliendo & Kopeinig, 2008).

2.4 Data and Model Specification

2.4.1 Data

We compile a unique firm-level data set that combines financial data for European firms with a global M&A database covering the years 2000-2007. The financial data is taken from the Amadeus database published by Bureau van Dijk, which provides information on firms' balance sheet and profit and loss accounts for up to ten years. The data is collected from company reports which are supplemented by specialized regional information providers. Amadeus has been used in numerous empirical studies on FDI (see Helpman et al., 2004; Budd et al., 2005, as exam-

[8]The propensity-score matching and covariate balance testing is carried out using Leuven & Sianesi's (2003) software psmatch2 in STATA® 10.

ples). Combining several updates of the Amadeus database, we are able to consider entry and exit of firms and thus, a broader sample of firms to identify acquirers in cross-border deals.[9] For the empirical analysis we use unconsolidated company accounts. This allows us to separate acquirer's from target's operations after an acquisition and to analyze the effects of cross-border M&As on *domestic* sales, employment, and productivity. One limitation of the Amadeus database is that values for key variables like sales, employment, or financial indicators are missing for some companies. Nonetheless, it has been found that the sectoral and aggregate distribution of firm size and growth rates follows those from national labor force surveys and the OECD Stan database (see Messina & Vallanti, 2007, for instance). The only constraint is that the Amadeus database has an incomplete coverage of very small firms as most firm-level data sets. However, as cross-border M&As are usually not undertaken by small companies, this is of minor relevance for this application as shown in the robustness section.

We merge the observations from Amadeus with the transaction data from our second data source, the Zephyr database, an M&A database from the same provider. Zephyr includes data on M&As, IPOs, joint ventures, and private equity transactions and provides information about the date and value of a deal, the source of financing as well as a description of the type of transaction and the firms involved in the deal. We are thus able to identify the sequent foreign investments and to reconstruct the growing international commitment of firms. The data are collected from company reports, regional information providers, consulting firms, investment banks, firms' web pages and press releases. Compared to other M&A data sources like Thompson Financial Securities data, the Zephyr database has the advantage that there is no minimum deal value for a transaction to be included in the data set.[10] While the database does certainly not contain all M&A transactions worldwide, we are confident that our data covers all M&As of firms that appear in our data set, since Bureau van Dijk updates the ownership structure of all com-

[9] Update numbers 88, 113, 136, 146 and 168 are used. Although Amadeus provides information on subsidiaries, this information is only available at one point in time for each update. Further, the data does not allow for a definite distinction between newly founded subsidiaries and existing firms that have been acquired. Therefore, we merged the firms from Amadeus with the Zephyr database to gather information on M&A deals.

[10] When comparing aggregate statistics derived from own calculations of the Zephyr database with those from Thompson financial data as used in Brakman et al. (2007a), we found that the coverage of transactions with a deal value above 10 million US$ is very similar. Calculations are available upon request.

panies covered in the Amadeus database regularly. Due to the various channels of information, the biggest and economically most relevant M&As should be covered by the Zephyr database.

The data structure of this new combined European firm-level data set allows us to focus explicitly on cross-border M&As. Since data availability varies considerably across countries; we restrict our analysis to firms from the U.K. and France. Both countries belong to the top five countries with respect to the number of acquiring firms in international deals (Brakman et al., 2007a) and they are characterized by several institutional differences. While the former exhibits a market-based financial system and flexible labor markets, France features a more bank-based financial system and highly rigid labor markets.

The FDI definition applied by the OECD (1999) refers to investments of at least 10% in order to separate portfolio investments from investments with a lasting interest in and relevant influence on the foreign firm. For the purpose of this application, we consider only deals where a substantial change in the stakes hold is involved as it is usual in the M&A literature. The presented results refer to M&As, in which the stake controlled rises from below to above 25% as firms gain at least a blocking minority.

In our sample, we delete enterprises with a median value of annual sales and total assets below €2 million based on all available firm-year observations, and firms active in the primary sector (NACE Revision 1.1 two-digit industry codes 1-14) as these enterprises are usually not taking an active part in cross-border M&As. We further deleted holding companies (NACE 7415), firms from the public sector (NACE 75, 91), and financial companies (NACE 65-67) as the definition of output or sales and hence any measure of total factor productivity in financial companies is not comparable to other firms. Inspecting the growth rates of variables like firm size and number of employees, we delete large outliers at both ends of the distribution as they could indicate an unreported merger. After applying standard cleaning procedures[11] and restricting the sample to observations that have data for all necessary variables in at least four consecutive years, we are left with 270 French and 646 British firm-year observations with at least one cross-border deal recorded.

[11] We deleted observations with implausible values such as negative input factors or values of tangible or intangible assets that exceed total fixed assets, and with growth rates larger than the 199th and smaller than the first 200-quantile.

2.4.2 Model specification

We evaluate the impact of international acquisitions on several outcome variables. Growth rates in the capital stock (measured as tangible fixed assets), sales, and employment are analyzed to evaluate whether international acquisitions complement or substitute domestic activity. Total factor productivity (TFP) is considered as a further outcome variable to investigate whether cross-border M&As lead to an increase or decrease in domestic efficiency. We implement the Olley & Pakes' (1996) estimation algorithm, where we use investments to control for unobserved productivity shocks that induce a simultaneity problem in TFP estimation. This method is restricted to observations with strictly positive investment in order to guarantee a necessary invertability condition.[12] We calculate TFP for all observations with sales, labor, and capital figures available.

Regarding the choice of control variables in the logit model, heterogeneous firm models like Melitz (2003) and Helpman et al. (2004) suggest a systematic selection into foreign investment activity according to the firms' productivity levels. To control for the selection of more productive firms into foreign markets we include the level of TFP before the acquisition.

We include the log of the number of employees as a measure of firm size to capture the firms' ability to realize economies of scale as well as their capacity of taking risks through internal diversification. The log average wage (total labor costs divided by the number of employees) accounts for different skill structures of the labor force. The log capital stock captures differences in the production process and controls for the fact that multinational firms usually have a higher capital intensity than domestic firms. Further, as an R&D proxy, we control for the share of intangible assets in non-financial fixed assets, as this may affect domestic growth as well as the returns to acquisitions and should account for the importance of knowledge and technology for acquisitions. The working capital ratio defined as the ratio of net current assets to total assets reflects the firms' liquidity and captures the ability to raise funds for an international acquisition. We include past sales growth to capture differing domestic growth paths between acquirers and other firms to avoid a spurious correlation between domestic growth and acquisitions.

[12] The alternative estimation strategy using material inputs instead of investment as suggested in Levinsohn & Petrin (2003) is not an option as this variable is not available for the U.K. sample. However, we found that measures of TFP constructed with materials instead of investment in France were very similar.

The firms' internationalization status and past M&A activity before the deal are captured by an exporting dummy for the previous year, and dummy variables for previous national and cross-border deals. These variables take the value one if the firm had acquired at least one national or foreign target in the three years before the deal, respectively. Further, a variable with three categories that reflects the change in the number of foreign subsidiaries (no change, increase, or decrease in the number of foreign subsidiaries owned) is included as proxy for greenfield investment.

The age of a firm in years can be interpreted as a reflection of learning (Jovanovic, 1982) and is included as the logarithm of the number of years since incorporation as a further control for growth potentials and experience. In addition, a dummy controlling for the legal form equals one if the acquirer is a public limited company. Finally, differences in technological opportunities and the competitive environment are accounted for by industry dummies at the NACE two-digit industry level. A set of time dummies captures macroeconomic factors such as changes in the business cycle or exchange rate movements. All variables are measured one period before the cross-border M&A.

2.5 Results

Results from the logit estimation for the probability to invest abroad are shown in table 2.1. A higher firm size in terms of employment or capital stock makes it more likely to engage in an international acquisition. The positive coefficient for sales growth shows that firms that invest abroad display higher domestic growth rates before the acquisition. The working capital ratio coefficient indicates that insufficient internal finance could be an impediment to cross-border M&As. International acquirers seem to have higher innovation potentials and employees with higher skills as indicated by the positive coefficients for intangible assets and wages, respectively. This supports the idea of technology and knowledge as a driving factor for cross-border M&As.

Past M&A activity – both national and international – appears to be an important predictor of cross-border M&As in subsequent periods. The same is true for changes in the number of foreign subsidiaries owned by the firm and previous export activities - although this effect is only significant for British firms. This seems plausible, as the knowledge of a firm gained in earlier operations at a global stage reduces uncertainties related to foreign market entry and makes the successful realization of cross-border M&As more likely. The exporting status of French firms does not explain further international activity significantly. One possible explanation is that differences in the average firm size between acquirers and non-acquirers are much more pronounced in the U.K. as can be seen in table 2.2 and 2.3. These tables also show that the differences in the fraction of exporters between the unmatched groups are also much larger in the British sample. Foreign-owned firms have a lower probability to invest abroad, probably since they already have access to foreign markets and technologies. So far, the results are in line with the expectations.

Surprisingly, TFP has no significant effect on the probability of cross-border acquisitions in the case of French firms, while British firms that engage in acquisitions seem to be less productive conditional on all other regressors. This does not necessarily contradict the results from the FDI literature predicting a positive association between a firm's productivity and its FDI propensity. The reason is the inclusion of further variables as proxies for skills and innovation in our estimation equation apart from TFP levels. Those variables are important determinants of firm heterogeneity and productivity differences and are positively correlated with foreign market entry. Tables 2.2 and 2.3 show that unconditional on these control variables firms that engage in cross-border M&A are significantly more productive.

The success of the matching procedure is documented in tables 2.2 and 2.3. The means of the covariates used in the logit equation of the unmatched sample are compared in order to quantify the ex ante differences between acquirers and the comparison group. Selection into treatment is reflected in almost all variables. The matching procedure is able to reduce a substantial amount of bias resulting from differences in the observed covariates. As the test statistics show, the differences between the treatment group and the matched control group are small and insignificant for all variables used for the estimation of the propensity score. Most importantly, there is practically no difference in the propensity score between the two groups within each country, which is confirmed by an inspection of the shape of the propensity score distribution of both groups (compare figures 2.1 and 2.2). There, we also see that imposing the common support condition does not reduce the sample significantly (six French and two British acquirers are dropped).

Table 2.4 displays the results from the difference-in-differences estimation for the various outcome measures. Compared to other firms, both French and British international acquirers realize higher output growth. Overall, cross-border acquisitions do not seem to substitute domestic production, but they are associated with higher domestic sales growth in both countries. This complementarity between foreign and domestic activity is accompanied by significant faster growth of capital and employment. The results differ across countries, however, when it comes to the resulting productivity effects. The growth of TFP is about 4% and 7% larger for French firms that engage in international acquisitions in the year of the deal and in the first year after the deal, respectively, compared to firms that do not engage in cross-border acquisitions. This difference becomes insignificant after two years, however. British firms that engage in cross-border acquisitions do not achieve significantly higher growth in TFP. While the size of the effects on sales and employment are comparable to each other, the capital growth rate is even higher, resulting in an insignificant TFP effect in the U.K. sample.

The results indicate that cross-border acquisitions and domestic activity are complements. A possible explanation is that cross-border M&As provide access to new markets, which increases the intensity of headquarter activities such as marketing, R&D, product development, and administration in the home country which support both foreign and domestic production. The returns to these investments generally increase with the volume of sales over which costs can be spread (see, for instance, Cohen & Klepper, 1996). An alternative interpretation is that international acquisitions reallocate assets and production from less efficient targets to more efficient acquiring firms as argued by Neary (2007).

Regarding the magnitude of our estimated effects, we estimate effects on sales growth between 8% and 23% for a three-year interval. For comparison, Wagner (2002) estimates effects of starting to export on firm size of around 13%. Desai et al. (2009) find that an expansion of foreign sales by 1% point is associated with increased domestic growth of 0.3% points. Thus, the magnitude of our estimated effects appear to be plausible. The effects on TFP growth for French firms of about 4% are also similar to estimated effects of other types of foreign market expansion or organizational changes. For instance, Blalock & Gertler (2004) find that after firms start to export their productivity increases by 2% to 5% and productivity effects of changes in workplace practices have been estimated in the range of 5% to 14% (Black & Lynch, 2001). Given the size of the investment, comparable productivity effects of cross-border M&As seem not unreasonable.

Irrespective of the positive association between cross-border M&As and domestic activity on average, one could fear that there are negative effects on domestic production and employment for certain types of investments. As stressed previously, results might vary depending on the underlying motivation for the deal. Thus, we divide the sample with the aim to discriminate between different types of deals and uncovering potential heterogeneity in the results. Doing this, we also try to shed some further light on the observed cross-country differences in the productivity result, where the composition of the deals could drive the observed effects on average. For this purpose, we take a closer look at the industry composition of the deals. One concern is that negative effects on domestic growth are more likely in manufacturing than in services, because exporting or a fragmentation of the production process is less feasible in most service sectors. Another dimension of industry heterogeneity we consider is technological intensity. Access to foreign knowledge and technologies is probably an important factor behind cross-border acquisitions in industries that are technology-intensive and this might lead to differential impacts on domestic efficiency and growth. We use an industry classification that groups activities in the manufacturing and service sector according to the importance of technology and knowledge.[13] Tables 2.6 and 2.7 show the industry composition of cross-border deals in France and the U.K, respectively. While in both countries international acquisitions happen most frequently in knowledge-intensive service industries, acquisitions of French firms are even more biased towards knowledge-intensive service sectors, where almost half of all acquisitions belong to in our estimation sample.

In France, the positive effect on sales is quite robust across the four subgroups. Again, we cannot find any evidence for a negative employment effect. The positive productivity effects for French firms seem to be predominantly driven by deals of acquirers in technology and knowledge-intensive industries, where the productivity differences are most pronounced and significant. The point estimates for other services are even negative, but insignificant. For British firms, sales and production inputs grow significantly faster for acquiring firms within all types of industries. We observe a significantly positive productivity effect of international acquisitions only in high-tech manufacturing.

[13]The classification was made on the basis of the sector approach by the European Commission (Eurostat) which classifies industries according to the ratio of R&D spending to value added.See, for instance, http://epp.eurostat.ec.europa.eu/cache/ITY_SDDS/Annexes/htec_esms_an2.pdf. We classified manufacturing industries as high-tech if they are defined as ‘High Technology’ or ‘Medium High Technology’ by Eurostat and classified knowledge-intensive services according to Eurostat.

Hence, in both countries, there are industries, where cross-border acquirers show a higher TFP growth rate and this seems to be mainly the case in high-tech industries. One possible explanation is that in technology-intensive industries, acquirers focus on access to complementary foreign technologies and knowledge that improve domestic efficiency. Investments in low technology sectors might be undertaken to gain access to the target's market and products rather than to acquire complementary technologies. This view is supported if we take another look at table 2.5. Overall, 11% of the French and 28% of the British acquirers invest in the U.S. In high-tech manufacturing sectors, however, this share is highest in each of the two countries. Thus, precisely in the sectors with an above average share of deals in the most technologically advanced region, we find positive productivity effects supporting the view of technology-seeking motives for these deals.

The tests of equality of treatment effects in the last columns of 2.6 and 2.7 show that cross-industry differences in productivity effects are statistically significant in France and weakly so for British firms. It seems that heterogeneity in the productivity effects across countries can mainly be explained by the different composition of deals across industries.

Technology sourcing might be a less important motive in industries with a low technological intensity, where foreign market access is probably the dominant motive for cross-border M&As. Market access may lead to increased demand for production and headquarter activities in the home country, but this does not necessarily affect efficiency of production in terms of output per employee or unit of capital.

The tests for treatment effect heterogeneity show that industry differences in the effects on sales and employment growth are in some cases statistically significant for British firms. With one exception, differences in the effects on growth rates are insignificant for French firms even at the 10% level. Again, the results suggest that differences in treatment effect heterogeneity across countries – especially regarding employment growth – are to some extent due to the differing composition of deals across industries.

Still, the estimated effects on employment growth seem to be somewhat larger in the U.K. There are several possible alternative explanations for this, which are not mutually exclusive. First, labor markets are more rigid in France and hence, French acquirers might in some cases be more likely to cancel explicit and implicit contracts with employees after an acquisition (Shleifer & Summers, 1998). This effect might dampen the overall positive impact of foreign expansion in French firms (see e.g. Gugler & Yurtoglu, 2004, and our discussion in section 2). Further, British firms are more likely to engage in full acquisitions than French firms in our sample (90% versus 50%) and finally, they more often invest in larger target markets like the U.S., both of which might result in higher feedback effects.[14]

Another dimension of heterogeneity is the distinction between horizontal and vertical acquisitions. Foreign market access is the goal of horizontal foreign investments. We use deals in which acquirers and targets operate in the same 2-digit industry to approximate this type of investments. The remaining deals are classified as unrelated as most of those deals are probably conglomerate acquisitions rather than vertical investments. The separate estimation of related and unrelated deals does not extract differential behavior clearly. Our main result, the positive effect of cross-border M&As on domestic growth seems to hold both for related and unrelated acquisitions.[15] Although this distinction is quite often applied in empirical work, defining within-industry deals as horizontal FDI as opposed to cross-industry investment is quite a crude approximation that probably does not reflect perfectly the differences in the motives for the deals (for a discussion, see Alfaro & Charlton, 2009).[16]

While both theoretical work and the evidence presented so far suggest improved access to foreign markets and technologies as a main explanation for the results found, there could be alternative stories. If acquirers use mechanisms such as transfer pricing to shift profits the results might not correspond to actual changes in real economic activity. While this is unlikely to affect our estimated effects for employment and the capital stock, it might bias our results for sales and produc-

[14]Due to the small number of cross-border acquisitions, we refrain from separating treatment effects across industries, full acquisitions and target markets simultaneously, which would be necessary to disentangle the various explanations formally.

[15]Results are therefore not reported, but available upon request.

[16]Another way to approximate the type of investment would be the target country or region. Cost motives should lead to cross-border acquisitions in low-cost countries, whereas market-seeking motives can be assumed for investments in large, equally developed countries. Most French firms invest in other Western European countries for their economic, geographic, and cultural proximity. British firms prefer U.S. targets, where access to the technological frontier might be decisive in addition to the large market (compare the first two columns in table 2.5). Hence, factor costs do not seem to be a main driver of acquisitions in our sample. Splitting the sample according to the target regions does not generate any new insights as the number of observations for investment in low-cost countries is too small.

tivity. However, incentives for transfer pricing are probably small in our sample, as most acquisition targets are located in countries in Western Europe and North America which have similar statutory corporate tax rates and accounting standards. Nonetheless, to investigate whether transfer pricing is an issue in our data set, we analyze whether tax payments change significantly after cross-border M&As similar to Egger et al. (2010). The reasoning is that if transfer pricing played an important role, we should see that tax payments are reduced significantly after a cross-border acquisition. Transfer pricing might be easier in technology and knowledge-intensive industries due to the higher share of intangible assets. Therefore we rerun the matching procedure with tax payments scaled by pre-acquisition sales to account for differences in firms size as an additional outcome variable for the four industry groups in France.[17] The results in table 2.8 show that 10 out of 12 estimated coefficients are insignificant. Only in one period we find a weakly significant positive association for knowledge intensive services and a weakly significant negative association for other services. Tax savings seem not to be very relevant in our sample, especially not in high-tech sectors. Thus, transfer pricing is not sufficient to explain the overall positive effects on sales growth and the heterogeneous effects on productivity across industries.

Yet another explanation for the estimated effects on domestic growth could be that cross-border M&As are part of a firm's general expansion strategy that includes both domestic and foreign investments leading to a spurious correlation between international acquisitions and domestic growth. To check whether this is a likely explanation for our results we use domestic M&As as an outcome variable. Results depicted in table 2.9 show no significant correlation between domestic and cross-border acquisitions for British firms, while there seems to be some correlation for French firms. However, the estimated effect is only weakly significant in the first period and changes its sign in later periods. All in all, the correlation seems to be rather unsystematic, hence, it seems unlikely that a simultaneous domestic expansion strategy is the predominant explanation for our results.[18] Finally,

[17] Unfortunately, tax payments are missing for most British firms in our sample. Hence, we do not report results for the U.K.

[18] Note that it is not implausible that cross-border M&As have some effect on the incentives to engage in domestic M&As. In many oligopolistic models the incentives for takeovers are increasing with market concentration and hence with previous M&As (see, for instance, Neary, 2007, for an application to cross-border M&As.). Firms might also be more likely to engage in further (domestic and foreign) M&As due to previous success and experience. In contrast, cross-border and domestic M&As might also be substitutes

we restrict the estimation sample to firms without additional domestic acquisitions in the same period or in the two years after the deal and adjust the control group accordingly. The results are basically unchanged (compare table 2.11 and table 2.10). The estimated effect on output growth is significant and positive in all specifications, and again no single negative effect shows up. It is thus unlikely that the results found are determined predominantly by firms with simultaneous acquisition in the domestic market.

Summing up, our results indicate that on average cross-border acquisitions yield higher domestic production and in some cases efficiency gains in the home country. Neither do we find that international acquisitions substitute domestic investment, nor are there adverse effects on employment growth for any of the two countries and in any of the industries and types of deals considered.

2.6 Robustness Checks

In this section, we provide several robustness checks regarding the estimated effects of cross-border M&As on the acquirers' domestic growth rates of output, employment, investment, and productivity using a difference-in-differences estimator in combination with propensity matching.

The first robustness check regards the definition of M&As. In the main specification we defined a cross-border M&A as an international transaction in which the share of the acquisition target's equity owned by the acquiring firm rises from below to above 25%. The estimated effects do practically not change considering deals where the acquirer obtains a majority interest after the acquisition (compare the first columns in tables 2.12 and 2.13).

A look at the distribution of the acquired stake reveals that there are quite a lot of deals with very small changes around one per cent only that stem from repeated share buyback activity. The two peaks of the distribution can be found at 50% and 100%. Thus we have only little variation across the two samples. We further checked whether firms with multiple acquisitions led to an overestimation of the average treatment effect. Calculating the effects for firms with only one acquisition per year separately - which includes the majority of our observations - changes the

due to limited financial resources and organizational capabilities.

results only slightly. The same holds true for the British sample if alternatively firms with the first acquisition after at least three years are considered, while the productivity effects disappears in the French case (see the second and last columns in tables 2.12 and 2.13 for France and the U.K., respectively).

A further decision that we have to make is the number of years that we follow the effects of the deals. In the main specification we estimated the effects of cross-border M&As on outcome variables in periods t, t+1, and t+2. On the one hand, potential restructuring measures might take some time to come into effect, so a longer time horizon would be an interesting extension. On the other hand, even the basic specification is already very data demanding. Including the third year after the deal in the analysis thus reduces the sample quite substantially. As a consequence, some of the effects are less precisely estimated and lose their statistical significance. All results, however, still indicate the same direction of the effects and a very similar magnitude and effects even increase in the third period after the deal (first columns of table 2.14 and 2.15).

Another robustness check relates to the problem of panel attrition. We check the consequences of relaxing the restriction of our main specification that only firms are included for which data is available in both periods after the deal (the second columns of tables 2.14 and 2.15). Again, the results are robust to this variation. Finally, although it is quite common to use the period before treatment, a potential concern could be the chosen reference period for the conditioning variables in the propensity score estimation. If the decision of firms to engage in international M&As is made quite in advance and firms use the pre-acquisition year for adjusting domestic production to the upcoming integration process, conditioning on variables measured two periods before the deal would be more appropriate. Hence, in this alternative specification, we drop the second year after the deal to keep enough observations. Results are still similar to the basic specification (see the last columns of tables 2.14 and 2.15).

The inclusion of the smallest firms in a country is another variation in the definition of the estimation sample. In our main specification we decided to exclude firms with a median value of annual sales and total assets below €2 million based on all available firm-year observations. However, removing this restriction and using all firms in the sample again does not change the results notably (see the second column in tables 2.16 and 2.17).

To check the robustness of our results for productivity, we use labor productivity (sales per employee) as an alternative productivity measure instead of total factor productivity (TFP). While the Olley & Pakes method used to construct a consistent TFP measure takes panel attrition and the endogeneity of production input factors into account, it critically hinges on functional form restrictions and the validity of instrumental variables. However, TFP and labor productivity are highly correlated in our estimation sample. Results using labor productivity as outcome variable are depicted in the last columns of tables 2.16 and 2.17. Not surprisingly, we find similar results as before.

A crucial assumption of the matching procedure we used for the estimation of the average treatment effect is the assumption of selection on observables. Hence, further robustness checks are performed to check the sensitivity of the results towards using different control variables. To account for possible differences in the growth trends of the two groups, we included the last year's sales growth as a conditioning variable in the estimation of the propensity score in the main specification. One could argue for the inclusion of past changes of all dependent variables of interest in order to control for varying trends in the evolution of the firms' productivity level, capital, or employment. Including all but one growth rates does not change our results notably (second columns of tables 2.16 and 2.17). Note, that we have to exclude one growth rate and one level to avoid multicollinearity problems as the TFP measure is a linear combination of the factor inputs and output. We excluded the TFP growth rate and the sales level. As sufficient liquidity is an important prerequisite for a firm to be able to finance a deal, we control additionally for changes in the liquidity measure one or two periods before the deal. The results show that our results are unaffected from these changes (compare table 2.18). All in all, these robustness checks indicate that the inclusion of a large number of controls in the logit estimation captures already a substantial part of the important differences between the two groups of firms.

Using a matching approach, the selection of an adequate control group is crucial for the interpretation of the results. In our main specification, the estimated effects are calculated as the differences between the treatment group of acquirers and the chosen control group of firms not involved in a cross-border deal in the years of the deal and after the deal. Thus, the control group includes firms that engage in greenfield investments and domestic M&As as well as firms without such investments. We estimate three alternative models each to check whether the results are robust to changes in the definition of the control group, in particular with respect to their domestic M&A and greenfield investment activity (compare table 2.19 and 2.20 for France and the U.K., respectively). The three alternative specifications are C1.) the control firms have no cross-border acquisition in t; C2.) the control firms have no cross-border and no domestic acquisition in t; and C3.) the control firms have no cross-border, no domestic acquisition and no change in the number of foreign affiliates in t. The results from these variations confirm our previous results: in the British sample, we get mainly unchanged results both in terms of statistical significance and magnitude of the effects. For France, the sales effect is strong and significant in all specifications, where the investment and employment effect is always positive and of similar magnitude, but loses its significance in some periods and specifications. As before, the productivity effect is less robust across specifications.

Although the results of the matching procedure seem to be robust to introducing further covariates, we cannot formally test the assumption of selection on observables. However, it is possible to calculate the magnitude of the bias that would be necessary to outweigh our estimated treatment effects. For this purpose we display Rosenbaum bounds, which indicate the minimum value by which an unobserved factor would have to change the odds ratio of a matched pair *i* and *j* $\frac{P(CB_{it}=1|X_{it})(1-P(CB_{it}=1|X_{it}))}{P(CB_{jt}=1|X_{jt})(1-P(CB_{jt}=1|X_{jt})}$ to reduce the significance of our estimated average treatment effect on the treated below a certain confidence level. Given conventional levels of significance, the critical values for domestic sales, capital and employment growth vary between 1.2 for capital growth for French firms and above 2.0 for employment growth in the British sample (tables 2.21 and 2.22). A factor that could change the odds ratio even by a factor of the lower bound of 1.2 in France must have a larger effect on the probability of an acquisition than an increase of the number of employees in the pre-acquisition period by 50% or an increase in the capital stock by 70%. Transforming the estimated coefficients of the logit model into odds ratios led to values of 1.279 for capital and 1.384 in the French sample. The critical values for TFP are as expected quite low, as they were only partly significant in our main specifications. Note also that this factor must in addition completely determine the observed difference in the outcome variables of acquiring firms and the comparison group. While differences between acquirers and non-acquirers exceed these thresholds in our unmatched sample, these differences are eliminated by the choice of our control group. Given that our propensity score estimates control for a large set of covariates including the main determinants from the theoretical and empirical literature, we argue that it is unlikely that an omitted factor has such a large effect on both the propensity to engage in a cross-border acquisition and the domestic growth of sales, employment and capital. In conclusion, it does not seem very plausible that our estimated positive effects of cross-border acquisitions on domestic growth are entirely due to omitted variables.

Moreover, we investigate the robustness of our results to using alternative matching algorithms (see tables 2.23 and 2.24). In our baseline specification we use only one control observation as a match where the one with the closest propensity score is chosen irrespective of the actual distance. First, we implement caliper matching imposing a maximum distance of 0.1 for the difference in propensity scores within each matched pair. Second, some alternative matching algorithms that use a larger number of matches for each acquiring firm are applied to reduce the variance of the estimator. However, this comes at the cost of an increased potential bias as on average the matching quality is lower. We perform radius matching with a maximum bandwidth of 0.1, which uses all firms from the comparison group within a maximum distance in the propensity score of 0.1. Further, we show the results using three instead of only one nearest neighbor combined with a caliper of 0.1. The sensitivity of the results with respect to the primary matching criterion – the propensity score – are analyzed by the use of a Mahalanobis matching estimator that chooses a nearest neighbor not only with respect to the propensity score, but gives additional weight to a firm's industry, age and the year of acquisition, as these variables might be especially important determinants of firm growth. This comes at the cost of a large sample reduction as we lose several matches due to the common support condition. Next, some variants of a kernel matching estimator that use a weighted average of all firms in the comparison group to construct the counterfactual are applied (see the first two columns of tables 2.25 and 2.26). The weights for the kernel estimator are based on differences in the propensity score between acquirers and firms from the comparison group and a normal and alternatively a uniform kernel function. Using kernel functions, an important choice is the bandwidth of the estimator. Considering the implied trade-off between variance and potential bias, we reran the matching procedure with a bandwidth of 0.2 and 0.02 (columns three and four of tables 2.25 and 2.26). The estimations show that our main findings are robust to using alternative matching estimators. For both countries we find large and highly significant effects on the domestic growth of sales, employment and capital. Positive productivity effects only show up for French firms, but they are not significant in all cases.

The multiple robustness checks so far refer to the same estimation strategy. In addition, we finally apply a fixed effects estimator to our datasets. We run fixed effects panel regressions of the levels of the four outcome variables in t, t+1, and t+2 on a cross-border dummy variable. As control variables we use all lagged time-varying variables that were included in the logit estimation of the propensity score. In France, the output expansion effect and partly the labor effect are highly significant and of the same magnitude as before. All other coefficients point into the right direction, but as in other checks, they appear less robust in terms of statistical significance. The results for the British sample are mainly identical to the matching and difference-in-difference estimates (table 2.27).

2.7 Conclusion

Cross-border acquisitions occur more and more frequently and often involve tremendous deal values. These huge investments between countries stir up fears concerning the relocation of domestic economic activity in many countries, but also raise hope for strengthening the acquiring firms' position within an industry and internationally. This contribution provides first evidence on the effects of cross-border acquisitions on the investing firms' domestic performance. Our empirical analysis is based on a combination of matching techniques with a difference-in-differences estimator that is applied to a micro data set of firms from the U.K. and France, two European countries among the top five with the highest M&A activity in terms of the number of acquirers. Our main result shows that cross-border deals yield higher growth rates of domestic sales, employment, and capital in acquiring firms, which are in some cases accompanied by higher productivity growth.

We perform separate analyses for manufacturing and service industries and technology-intensive industries to uncover heterogeneous effects. Domestic sales growth is positively related to cross-border acquisitions in all industry types within both countries, and domestic employment growth and investment in the acquiring firm is not negatively affected in any case. We find significant effects on total factor productivity for technology-intensive industries only, which suggests that firms within these industries acquire complementary technologies abroad in line with theoretical work. The positive effect of international acquisitions on domestic activity might stem from increased domestic production that is used to serve newly entered foreign markets, and increased headquarter activities such as marketing and product development that can be applied to a larger production output after a foreign expansion. A variety of checks indicate that our results are unlikely to be explained by alternative mechanisms such as transfer pricing or a simultaneous expansion of domestic and foreign activities that are unrelated to the effect of cross-border M&As. These effects are robust towards different matching algorithms, definitions of the control group, and model specifications controlling not only for observed differences in a wide range of variables, but also for potentially diverging domestic growth paths between the group of acquiring firms and control units.

The positive effects on the investing firms should be taken into account when evaluating the welfare effects of cross-border M&As. Policy measures that mutually prevent international M&As between two countries might reduce growth and welfare in both countries since they impede access to foreign markets and technologies. For future research, it might be interesting to shed further light on the relation between the effects on target and acquiring firms in cross-border deals to assess their global economic consequences.

2.8 Tables

Table 2.1
Logit estimation – Dependent variable: at least one cross-border M&A deal.

	France		United Kingdom	
	β	SE	β	SE
TFP	0.0493	(0.1267)	-0.1382*	(0.0819)
Sales growth	0.6238**	(0.2665)	0.2391*	(0.1441)
Wages	1.4633***	(0.2214)	1.2289***	(0.1404)
Capital	0.2463***	(0.0663)	0.1476***	(0.0495)
Labor	0.3248***	(0.0799)	0.4056***	(0.0614)
Intangible assets	1.0796***	(0.2737)	1.6428***	(0.1833)
Working capital ratio	0.8664***	(0.3273)	1.5834***	(0.2271)
Exporter	0.1354	(0.1550)	0.5304***	(0.1010)
National deals	1.5082***	(0.1996)	0.7829***	(0.1180)
Cross-border deals	2.3501***	(0.1889)	1.7771***	(0.1204)
Δ foreign subsidiaries	1.4689***	(0.1718)	0.5442***	(0.0948)
Foreign owner	-1.0254***	(0.3027)	-0.8581***	(0.2346)
Legal form	0.8614***	(0.1668)	1.4631***	(0.1171)
Age	-0.0317	(0.0934)	-0.0586	(0.0519)
Industry dummies	yes		yes	
Time dummies	yes		yes	
N	107,878		104,202	
Pseudo-R^2	0.4194		0.4834	

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2.1
Propensity score density – France.

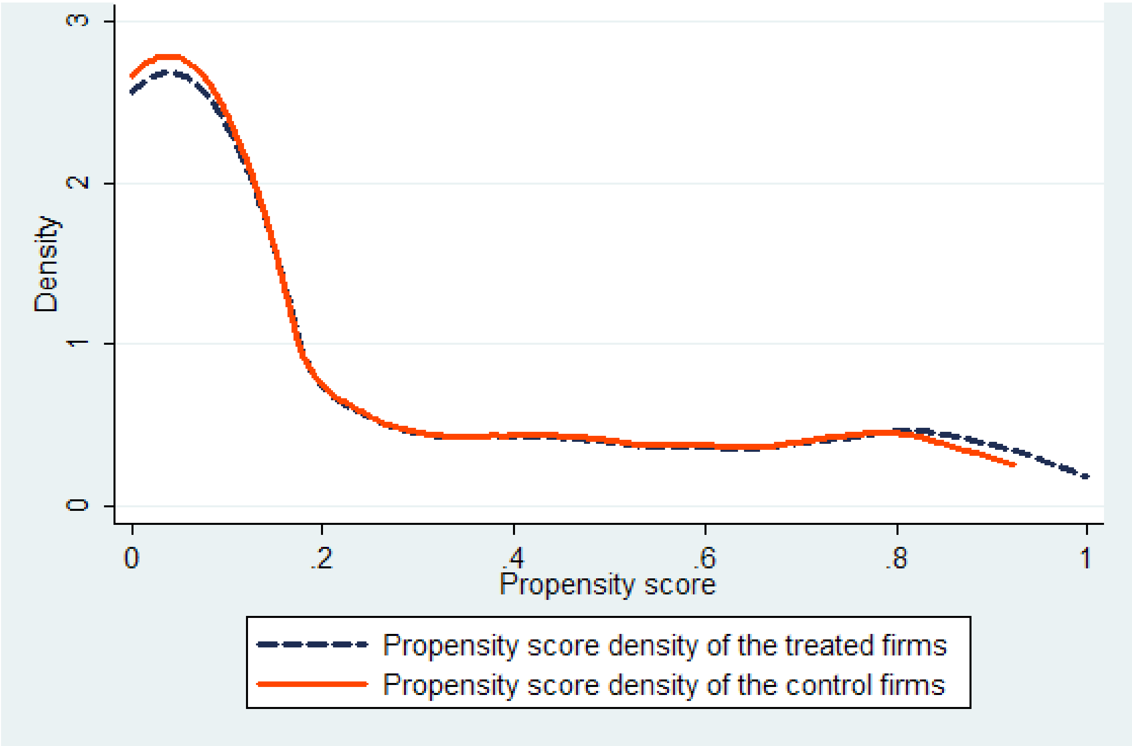

Table 2.2
Balancing test – France.

	Sample	Treated	Comparison	% bias	bias reduction	t-test equal means	p-value
TFP	Unmatched	1.129	0.750	52.0		8.65	0.000
	Matched	1.111	1.167	-7.7	85.2	-0.84	0.400
Wage	Unmatched	4.051	3.590	104.5		20.09	0.000
	Matched	4.038	4.019	4.3	95.9	0.47	0.640
Sales growth	Unmatched	0.099	0.051	18.6		3.41	0.001
	Matched	0.098	0.107	-3.4	81.6	-0.38	0.703
Capital	Unmatched	8.471	6.303	99.6		21.57	0.000
	Matched	8.398	8.623	-10.4	89.6	-1.01	0.315
Labor	Unmatched	5.609	4.047	96.4		22.74	0.000
	Matched	5.565	5.839	-16.9	82.5	-1.61	0.109
Intangible assets	Unmatched	0.326	0.190	46.7		8.36	0.000
	Matched	0.324	0.323	0.4	99.2	0.04	0.968
Working capital ratio	Unmatched	0.129	0.175	-18.3		-3.05	0.002
	Matched	0.131	0.162	-12.4	32.6	-1.50	0.135
Exporter	Unmatched	0.596	0.546	10.3		1.67	0.095
	Matched	0.598	0.598	0.0	100.0	0.00	1.000
National deals	Unmatched	0.322	0.007	94.0		61.87	0.000
	Matched	0.311	0.295	4.5	95.2	0.38	0.705
Cross-border deals	Unmatched	0.430	0.003	120.9		115.81	0.000
	Matched	0.417	0.383	9.7	92.0	0.80	0.425
Δ foreign subsidaries	Unmatched	0.474	0.025	102.0		40.18	0.000
	Matched	0.462	0.485	-5.2	94.9	-0.47	0.638
Foreign owner	Unmatched	0.052	0.106	-20.0		-2.87	0.004
	Matched	0.053	0.049	1.4	92.9	0.20	0.844
Legal form	Unmatched	0.785	0.346	98.6		15.14	0.000
	Matched	0.780	0.792	-2.6	97.4	-0.32	0.751
Age	Unmatched	3.189	2.964	26.8		4.80	0.000
	Matched	3.174	3.150	2.9	89.3	0.32	0.746
Propensity score	Unmatched	0.217	0.002	103.0		156.82	0.000
	Matched	0.201	0.201	0.1	99.9	0.01	0.992

Table 2.3
Balancing test – United Kingdom.

	Sample	Treated	Comparison	% bias	bias reduction	t-test equal means	p-value
TFP	Unmatched	1.085	0.980	12.9		2.92	0.004
	Matched	1.084	1.094	-1.2	90.5	-0.26	0.792
Wage	Unmatched	3.858	3.657	42.1		10.03	0.000
	Matched	3.859	3.880	-4.5	89.4	-0.85	0.394
Sales growth	Unmatched	0.099	0.062	10.5		2.78	0.006
	Matched	0.099	0.096	0.6	94.1	0.11	0.911
Capital	Unmatched	10.752	7.724	125.3		37.59	0.000
	Matched	10.742	10.887	-6.0	95.2	-0.93	0.351
Labor	Unmatched	7.457	4.713	148.2		48.77	0.000
	Matched	7.450	7.496	-2.5	98.3	-0.38	0.707
Intangible assets	Unmatched	0.413	0.076	122.3		42.14	0.000
	Matched	0.412	0.410	0.8	99.3	0.12	0.901
Working Capital	Unmatched	0.155	0.127	10.3		2.33	0.020
	Matched	0.156	0.152	1.5	85.7	0.32	0.753
Exporter	Unmatched	0.638	0.335	63.6		16.26	0.000
	Matched	0.637	0.643	-1.3	97.9	-0.23	0.817
National deals	Unmatched	0.489	0.029	123.5		68.31	0.000
	Matched	0.491	0.503	-3.3	97.3	-0.45	0.656
Cross-border deals	Unmatched	0.528	0.007	145.6		146.88	0.000
	Matched	0.526	0.489	10.4	92.9	1.34	0.181
Δ foreign subsidieries	Unmatched	0.370	0.012	74.5		56.85	0.000
	Matched	0.368	0.373	-1.0	98.7	-0.13	0.893
Foreign owner	Unmatched	0.037	0.113	-29.0		-6.06	0.000
	Matched	0.037	0.037	0.0	100.0	0.00	1.000
Legal form	Unmatched	0.728	0.083	174.1		59.04	0.000
	Matched	0.727	0.741	-3.8	97.8	-0.57	0.571
Age	Unmatched	2.992	2.866	12.7		3.59	0.000
	Matched	2.995	2.961	3.5	72.6	0.56	0.572
Propensity score	Unmatched	0.293	0.004	140.1		193.43	0.000
	Matched	0.291	0.291	0.0	100.0	0.01	0.996

Figure 2.2
Propensity score density – United Kingdom.

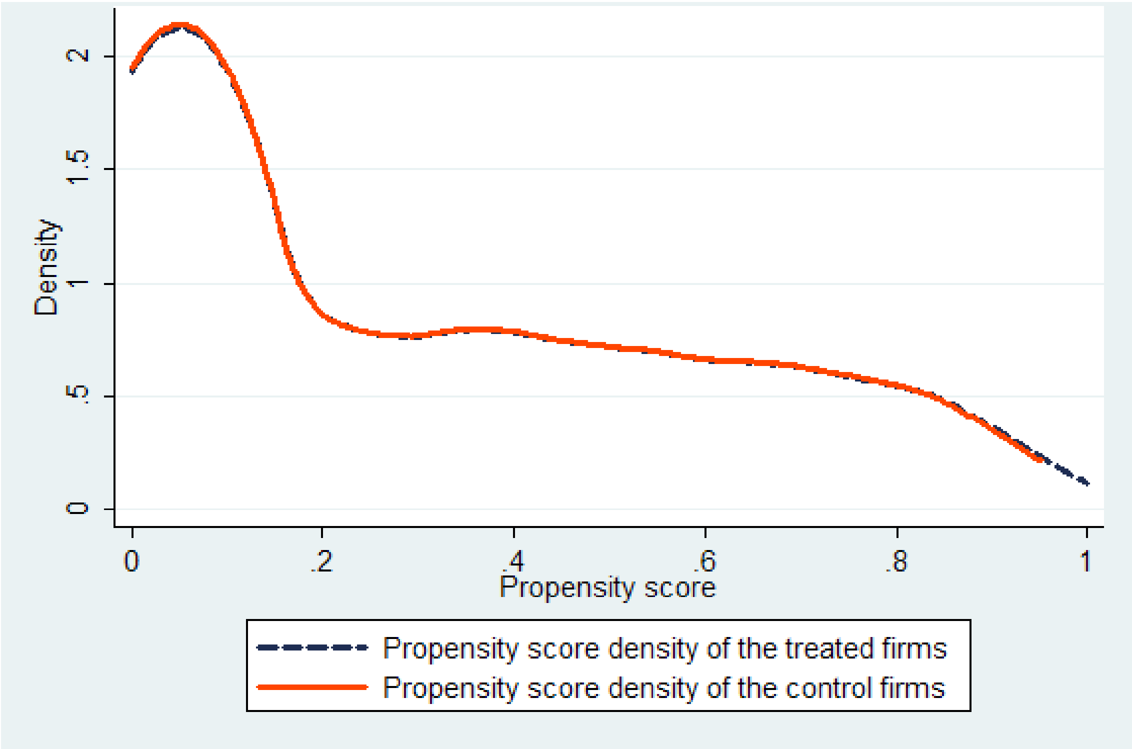

Table 2.4
Average effect of cross-border M&A on the acquirers' performance.

$y_{t+s} - y_{t-1}$		France		United Kingdom	
		DID	SE	DID	SE
Sales	t	0.0824***	(0.0206)	0.0935***	(0.0196)
	t+1	0.1455***	(0.0294)	0.1966***	(0.0300)
	t+2	0.1313***	(0.0364)	0.2358***	(0.0372)
Labor	t	0.0421***	(0.0156)	0.1045***	(0.0158)
	t+1	0.0710***	(0.0241)	0.1853***	(0.0240)
	t+2	0.0802**	(0.0318)	0.2320***	(0.0314)
Capital	t	0.0837**	(0.0363)	0.1451***	(0.0264)
	t+1	0.1493***	(0.0524)	0.1942***	(0.0378)
	t+2	0.1701***	(0.0641)	0.2596***	(0.0483)
TFP	t	0.0405**	(0.0178)	-0.0063	(0.0210)
	t+1	0.0743***	(0.0254)	0.0242	(0.0261)
	t+2	0.0507	(0.0320)	0.0188	(0.0261)
N on (off) support		264	(6)	644	(2)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.5
Number and percentage of deals according to target regions.

	All, absolute	All, relative	Manufacturing, hightech	Manufacturing, lowtech	Services, know-ledge intensive	Services, other
France						
EUW	141	53.4	40.5	48.8	52.4	69.8
US	29	11.0	23.8	11.6	9.5	3.8
CEE	15	5.7	4.8	9.3	4.0	7.5
other	42	15.9	21.4	20.9	14.3	11.3
multiple	37	14.0	9.5	9.3	19.8	7.5
	264	100.0	100.0	100.0	100.0	100.0
United Kingdom						
EUW	209	32.5	34.5	23.6	35.1	37.8
US	180	28.0	37.1	28.2	27.0	21.7
CEE	18	2.8	5.2	0.0	2.8	4.2
other	131	20.3	13.8	25.3	19.4	21.0
multiple	106	16.5	9.5	23.0	15.6	15.4
	644	100.0	100.0	100.0	100.0	100.0

Table 2.6
Average effect of cross-border M&A on the acquirers' performance by industry type – France.

		Manufacturing, hightech		Manufacturing, lowtech		Services, knowledge intensive		Services, other		Heterogeneous effects
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE	DID	SE	DID	SE	p-value
Sales	t	0.0709*	(0.0361)	0.0625	(0.0504)	0.1141***	(0.0323)	0.0325	(0.0334)	0.3733
	t+1	0.1865***	(0.0565)	0.1124*	(0.0614)	0.1645***	(0.0428)	0.0948*	(0.0549)	0.6026
	t+2	0.1042*	(0.0608)	0.1584**	(0.0761)	0.1564***	(0.0525)	0.0711	(0.0716)	0.7450
Labor	t	0.0082	(0.0246)	0.0525	(0.0366)	0.0392	(0.0251)	0.0672**	(0.0320)	0.4858
	t+1	0.0604*	(0.0324)	0.0746*	(0.0442)	0.0454	(0.0387)	0.1375***	(0.0458)	0.4506
	t+2	0.0216	(0.0622)	0.1537**	(0.0599)	0.0557	(0.0462)	0.1254*	(0.0730)	0.3854
Capital	t	0.0296	(0.0742)	0.0213	(0.0780)	0.0664	(0.0533)	0.2184***	(0.0689)	0.1675
	t+1	0.0750	(0.0951)	-0.0026	(0.0953)	0.1899**	(0.0761)	0.2347**	(0.0926)	0.2474
	t+2	-0.0044	(0.1165)	0.0544	(0.1037)	0.1891**	(0.0917)	0.3571***	(0.1065)	0.0903
TFP	t	0.0618*	(0.0326)	0.0160	(0.0303)	0.0758**	(0.0293)	-0.0403	(0.0306)	0.0328
	t+1	0.1295**	(0.0505)	0.0486	(0.0500)	0.1124***	(0.0389)	-0.0394	(0.0422)	0.0271
	t+2	0.0860	(0.0534)	0.0228	(0.0744)	0.0955*	(0.0500)	-0.0612	(0.0544)	0.1422
N		42		43		126		53		

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heterogeneous effects: p-value of an F-test on equality of coefficients of industry interaction terms. Industry classification based on NACE two-digit industry code. Manufacturing: 15-37. Hightech: 24, 29, 31, 33-35. Knowledge intensive services: 61, 62, 64, 70-74. Other services: 45, 50-52, 55, 60, 63.

Table 2.7
Average effect of cross-border M&A on the acquirers' performance by industry type – United Kingdom.

		Manufacturing, hightech		Manufacturing, lowtech		Services, knowledge intensive		Services, other		Heterogeneous effects
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE	DID	SE	DID	SE	p-value
Sales	t	0.0779**	(0.0353)	0.0216	(0.0276)	0.1457***	(0.0353)	0.1163***	(0.0280)	0.0239
	t+1	0.1997***	(0.0575)	0.0986**	(0.0490)	0.2807***	(0.0533)	0.1892***	(0.0381)	0.0950
	t+2	0.2607***	(0.0625)	0.1171*	(0.0606)	0.3104***	(0.0656)	0.2499***	(0.0484)	0.1477
Labor	t	0.0626**	(0.0284)	0.0504**	(0.0217)	0.1664***	(0.0269)	0.1131***	(0.0250)	0.0047
	t+1	0.1374***	(0.0420)	0.0957**	(0.0374)	0.2993***	(0.0413)	0.1649***	(0.0349)	0.0026
	t+2	0.1459***	(0.0498)	0.0950*	(0.0490)	0.3896***	(0.0515)	0.2357***	(0.0498)	0.0002
Capital	t	0.1141**	(0.0502)	0.1511***	(0.0342)	0.1900***	(0.0447)	0.0967***	(0.0372)	0.3996
	t+1	0.2100***	(0.0745)	0.1939***	(0.0515)	0.2542***	(0.0654)	0.0932	(0.0657)	0.3613
	t+2	0.2456***	(0.0885)	0.2615***	(0.0684)	0.2925***	(0.0839)	0.2203***	(0.0833)	0.9415
TFP	t	0.0163	(0.0211)	-0.0321	(0.0227)	-0.0102	(0.0242)	0.0126	(0.0223)	0.3842
	t+1	0.0673	(0.0426)	0.0031	(0.0392)	0.0063	(0.0347)	0.0413	(0.0272)	0.5979
	t+2	0.1185***	(0.0432)	0.0174	(0.0482)	-0.0440	(0.0428)	0.0324	(0.0377)	0.0652
N		116		174		211		143		

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heterogeneous effects: p-value of an F-test on equality of coefficients of industry interaction terms. Industry classification based on NACE two-digit industry code. Manufacturing: 15-37. Hightech: 24, 29, 31, 33-35. Knowledge intensive services: 61, 62, 64, 70-74. Other services: 45, 50-52, 55, 60, 63.

Table 2.8
Average effect of cross-border M&A on the acquirers' tax per sales – France.

		Manufacturing, hightech		Manufacturing, lowtech		Services, knowledge intensive		Services, other		Heterogeneous effects
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE	DID	SE	DID	SE	p-value
Tax	t	-0.0068	(0.0067)	0.0517	(0.0464)	0.0060	(0.0204)	0.0605	(0.0419)	0.2433
	t+1	-0.0016	(0.0085)	-0.0193	(0.0220)	0.0332*	(0.0187)	-0.0313*	(0.0164)	0.2331
	t+2	0.0072	(0.0068)	0.0013	(0.0100)	-0.0276	(0.0179)	-0.0046	(0.0129)	0.3144
N		42		43		117		51		

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heterogeneous effects: p-value of an F-test on equality of coefficients of industry interaction terms. Industry classification based on NACE two-digit industry code. Manufacturing: 15-37. Hightech: 24, 29, 31, 33-35. Knowledge intensive services: 61, 62, 64, 70-74. Other services: 45, 50-52, 55, 60, 63.

Table 2.9
Average effect of cross-border M&A on acquirers' domestic deals.

		France		United Kingdom	
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE
Domestic	t	0.072*	(0.0396)	0.045	(0.0340)
Acquisitions	t+1	-0.0568	(0.0348)	0.0264	(0.0313)
	t+2	-0.0758**	(0.0359)	0.000	(0.0305)
N on (off) support		264	(6)	644	(2)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.10
Average effect of cross-border M&A on the acquirers' performance with different control groups – France.

		Specification T1		Specification T2		Specification T3	
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE	DID	SE
Sales	t	0.0561***	(0.0188)	0.0739***	(0.0232)	0.0495**	(0.0201)
	t+1	0.1162***	(0.0260)	0.0901***	(0.0323)	0.0788***	(0.0279)
	t+2	0.1071***	(0.0379)	0.1364***	(0.0406)	0.1005***	(0.0332)
Labor	t	0.0394**	(0.0162)	0.0302	(0.0201)	0.0067	(0.0143)
	t+1	0.0546**	(0.0240)	0.0609**	(0.0257)	0.0464*	(0.0244)
	t+2	0.0983***	(0.0336)	0.0837**	(0.0412)	0.0787**	(0.0337)
Capital	t	0.0418	(0.0318)	0.0030	(0.0390)	0.0278	(0.0598)
	t+1	0.138***	(0.0505)	0.0651	(0.0632)	0.0972	(0.0732)
	t+2	0.1736***	(0.0586)	0.0360	(0.0694)	0.1343*	(0.0751)
TFP	t	0.0195	(0.0168)	0.0478***	(0.0162)	0.0419**	(0.0167)
	t+1	0.0598***	(0.0224)	0.0334	(0.0280)	0.0322	(0.0264)
	t+2	0.0107	(0.0296)	0.0621*	(0.0351)	0.0237	(0.0339)
N on (off) support		204	(14)	185	(9)	162	(13)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Specification T1: control group of firms without cross-border acquisition, national deal, in t, cross-border acquirers without national deals in t.
Specification T2: control group of firms without cross-border acquisition or national deal in t and t+1, cross-border acquirers without national deals in t and t+1.
Specification T3: control group of firms without cross-border acquisition or national deal in t, t+1, and t+2, cross-border acquirers without national deals in t, t+1, and t+2.

Table 2.11

Average effect of cross-border M&A on the acquirers' performance with different control groups – United Kingdom.

		Specification T1		Specification T2		Specification T3	
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE	DID	SE
Sales	t	0.0907***	(0.0229)	0.0883***	(0.0324)	0.1136***	(0.0248)
	t+1	0.2057***	(0.0322)	0.1905***	(0.0383)	0.2131***	(0.0397)
	t+2	0.2488***	(0.0395)	0.1963***	(0.0516)	0.2687***	(0.0486)
Labor	t	0.104***	(0.0163)	0.118***	(0.0171)	0.1029***	(0.0205)
	t+1	0.1927***	(0.0234)	0.2187***	(0.0257)	0.1824***	(0.0283)
	t+2	0.2497***	(0.0317)	0.2598***	(0.0343)	0.2311***	(0.0389)
Capital	t	0.1564***	(0.0302)	0.1733***	(0.0318)	0.1724***	(0.0415)
	t+1	0.2104***	(0.0445)	0.2246***	(0.0475)	0.2434***	(0.0531)
	t+2	0.3039***	(0.0549)	0.2982***	(0.0600)	0.2854***	(0.0650)
TFP	t	-0.0093	(0.0202)	-0.0249	(0.0282)	0.0134	(0.0159)
	t+1	0.0258	(0.0236)	-0.0127	(0.0309)	0.0398	(0.0260)
	t+2	0.0136	(0.0276)	-0.0473	(0.0388)	0.0507*	(0.0293)
N on (off) support		461	(7)	381	(7)	382	(5)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Specification T1: control group of firms without cross-border acquisition, national deal in t, cross-border acquirers without national deals in t.

Specification T2: control group of firms without cross-border acquisition or national deal in t and t+1, cross-border acquirers without national deals in t and t+1.

Specification T3: control group of firms without cross-border acquisition or national deal in t, t+1, and t+2, cross-border acquirers without national deals in t, t+1, and t+2.

Table 2.12

Average effect of cross-border M&A on the acquirers' performance using alternative specifications I – France.

		Deals where stake hold rises to more than 50%		Acquirers with only one deal per year		Acquirers with the first deal after at least three years	
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE	DID	SE
Sales	t	0.0771***	(0.0220)	0.0712***	(0.0245)	0.0814**	(0.0321)
	t+1	0.0932***	(0.0270)	0.1241***	(0.0356)	0.1420***	(0.0468)
	t+2	0.1119***	(0.0330)	0.1090**	(0.0444)	0.1204**	(0.0582)
Labor	t	0.0346*	(0.0179)	0.0375**	(0.0188)	0.0607***	(0.0230)
	t+1	0.0343	(0.0244)	0.0603**	(0.0291)	0.1043***	(0.0361)
	t+2	0.0328	(0.0317)	0.0677*	(0.0380)	0.0980**	(0.0493)
Capital	t	0.0429	(0.0369)	0.0921**	(0.0437)	0.0851	(0.0564)
	t+1	0.1036**	(0.0523)	0.1559**	(0.0625)	0.1148	(0.0816)
	t+2	0.1331**	(0.0607)	0.1474*	(0.0761)	0.1208	(0.0999)
TFP	t	0.0441**	(0.0244)	0.0327	(0.0214)	0.0235	(0.0275)
	t+1	0.0529**	(0.0311)	0.0616**	(0.0311)	0.0446	(0.0400)
	t+2	0.0691**	(0.0311)	0.0408	(0.0393)	0.0280	(0.0506)
N on (off) support		265	(3)	210	(2)	154	(0)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.13
Average effect of cross-border M&A on the acquirers' performance using alternative specifications I – United Kingdom.

		Deals where stake hold rises to more than 50%		Acquirers with only one deal per year		Acquirers with the first deal after at least three years	
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE	DID	SE
Sales	t	0.1115***	(0.0190)	0.1040***	(0.0253)	0.1120***	(0.0373)
	t+1	0.1815***	(0.0269)	0.2153***	(0.0389)	0.2240***	(0.0578)
	t+2	0.2387***	(0.0345)	0.2478***	(0.0485)	0.2656***	(0.0725)
Labor	t	0.1045***	(0.0153)	0.1094***	(0.0204)	0.1196***	(0.0299)
	t+1	0.1880***	(0.0227)	0.1853***	(0.0310)	0.1990***	(0.0457)
	t+2	0.2440***	(0.0297)	0.2245***	(0.0407)	0.2295***	(0.0607)
Capital	t	0.1723***	(0.0234)	0.1406***	(0.0345)	0.1646***	(0.0507)
	t+1	0.2284***	(0.0355)	0.2039***	(0.0496)	0.2165***	(0.0733)
	t+2	0.2899***	(0.0462)	0.2615***	(0.0637)	0.2587***	(0.0940)
TFP	t	0.0100	(0.0187)	0.0004	(0.0182)	-0.0020	(0.0272)
	t+1	0.0045	(0.0242)	0.0422	(0.0268)	0.0383	(0.0405)
	t+2	0.0093	(0.0242)	0.0371	(0.0334)	0.0508	(0.0508)
N on (off) support		638	(0)	475	(2)	305	(2)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.14
Average effect of cross-border M&A on the acquirers' performance with different time restrictions – France.

		Third period effects		No time restriction		$t-2$ control variables	
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE	DID	SE
Sales	t	0.0957***	(0.0285)	0.0746***	(0.0146)	0.0817***	(0.0254)
	t+1	0.146***	(0.0417)	0.0847***	(0.0234)	0.1273***	(0.0361)
	t+2	0.1641***	(0.0557)	0.1012***	(0.0349)		(0.0000)
	t+3	0.2341***	(0.0627)				
Labor	t	0.0518	(0.0351)	0.0448***	(0.0141)	0.0385**	(0.0176)
	t+1	0.0774*	(0.0433)	0.0596***	(0.0221)	0.0975***	(0.0274)
	t+2	0.08	(0.0547)	0.0857***	(0.0316)		(0.0000)
	t+3	0.0984	(0.0654)				
Capital	t	0.0505	(0.0604)	0.1213***	(0.0259)	0.1055***	(0.0410)
	t+1	0.1503*	(0.0802)	0.1611***	(0.0430)	0.113*	(0.0615)
	t+2	0.1728*	(0.0995)	0.1548***	(0.0585)		(0.0000)
	t+3	0.2013*	(0.1189)				
TFP	t	0.0477	(0.0316)	0.0277*	(0.0230)	0.0414*	(0.0335)
	t+1	0.0692*	(0.0384)	0.0225	(0.0308)	0.0358	(0.0000)
	t+2	0.0835*	(0.0458)	0.0169	(0.0308)		(0.0000)
	t+3	0.1357**	(0.0584)				
N on (off) support	t	176	(6)	502	(2)	147	(0)
	t+1			369	(1)		
	t+2			270	(0)		

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.15
Average effect of cross-border M&A on the acquirers' performance with different time restrictions – United Kingdom.

		Third period effects		No time restriction		$t-2$ control variables	
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE	DID	SE
Sales	t	0.1174***	(0.0228)	0.1011***	(0.0174)	0.08***	(0.0237)
	t+1	0.2087***	(0.0341)	0.1869***	(0.0265)	0.1929***	(0.0349)
	t+2	0.2423***	(0.0404)	0.2504***	(0.0373)		(0.0000)
	t+3	0.2879***	(0.0468)				
Labor	t	0.1135***	(0.0200)	0.0888***	(0.0126)	0.106***	(0.0182)
	t+1	0.2188***	(0.0312)	0.1848***	(0.0205)	0.2184***	(0.0281)
	t+2	0.2716***	(0.0374)	0.2607***	(0.0304)		(0.0000)
	t+3	0.3222***	(0.0438)				
Capital	t	0.1505***	(0.0292)	0.1539***	(0.0193)	0.155***	(0.0314)
	t+1	0.198***	(0.0441)	0.2004***	(0.0324)	0.2337***	(0.0462)
	t+2	0.2336***	(0.0557)	0.264***	(0.0466)		(0.0000)
	t+3	0.3017***	(0.0702)				
TFP	t	0.0096	(0.0160)	0.0142	(0.0189)	-0.0216	(0.0261)
	t+1	0.0072	(0.0231)	0.0145	(0.0254)	-0.0106	(0.0000)
	t+2	-0.0069	(0.0280)	0.0085	(0.0254)		(0.0000)
	t+3	-0.0094	(0.0315)				
N on (off) support	t	481	(4)	1,036	(0)	393	(0)
	t+1			843	(0)		
	t+2			653	(0)		

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.16
Average effect of cross-border M&A on the acquirers' performance using alternative specifications II – France.

		Including small firms		Including sales, capital, and employment growth		Dependent variable: labor productivity	
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE	DID	SE
Sales	t	0.0712***	(0.0214)	0.096***	(0.0230)	0.0824***	(0.0206)
	t+1	0.1242***	(0.0318)	0.1185***	(0.0293)	0.1455***	(0.0294)
	t+2	0.1284***	(0.0378)	0.134***	(0.0361)	0.1313***	(0.0364)
Labor	t	0.0327*	(0.0176)	0.0566***	(0.0192)	0.0421***	(0.0156)
	t+1	0.0586**	(0.0253)	0.0679***	(0.0263)	0.0710***	(0.0241)
	t+2	0.0788**	(0.0332)	0.1078***	(0.0323)	0.0802**	(0.0318)
Capital	t	0.0707*	(0.0361)	0.0846**	(0.0402)	0.0837**	(0.0363)
	t+1	0.1413***	(0.0505)	0.1461***	(0.0541)	0.1493***	(0.0524)
	t+2	0.1927***	(0.0636)	0.0877	(0.0649)	0.1701***	(0.0641)
TFP	t	0.0383**	(0.0185)	0.0415**	(0.0270)	0.0404**	(0.0263)
	t+1	0.0641**	(0.0274)	0.0501*	(0.0334)	0.0745***	(0.0332)
	t+2	0.0474	(0.0296)	0.0355	(0.0334)	0.0511	(0.0332)
N on (off) support		266	(4)	234	(5)	264	(6)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.17
Average effect of cross-border M&A on the acquirers' performance using alternative specifications II – United Kingdom.

$y_{t+s} - y_{t-1}$		Including small firms		Including sales, capital, and employment growth		Dependent variable: labor productivity	
		DID	SE	DID	SE	DID	SE
Sales	t	0.0988***	(0.0190)	0.0660***	(0.0191)	0.0935***	(0.0196)
	t+1	0.1929***	(0.0302)	0.1458***	(0.0284)	0.1966***	(0.0300)
	t+2	0.2288***	(0.0363)	0.1972***	(0.0358)	0.2358***	(0.0372)
Labor	t	0.1034***	(0.0159)	0.0758***	(0.0155)	0.1045***	(0.0158)
	t+1	0.2023***	(0.0251)	0.1661***	(0.0245)	0.1853***	(0.0240)
	t+2	0.2373***	(0.0323)	0.2189***	(0.0309)	0.2320***	(0.0314)
Capital	t	0.1593***	(0.0255)	0.117***	(0.0265)	0.1451***	(0.0264)
	t+1	0.2240***	(0.0371)	0.1997***	(0.0381)	0.1942***	(0.0378)
	t+2	0.2673***	(0.0491)	0.2639***	(0.0490)	0.2596***	(0.0483)
TFP	t	-0.0009	(0.0150)	-0.0071	(0.0226)	-0.0111	(0.0213)
	t+1	0.0038	(0.0208)	-0.0104	(0.0271)	0.0113	(0.0266)
	t+2	0.0067	(0.0247)	-0.0089	(0.0271)	0.0038	(0.0266)
N on (off) support		646	(2)	639	(4)	644	(2)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.18
Average effect of cross-border M&A on the aquirer's performance controlling for changes in liquidity.

		France				United Kingdom			
		Δ_{t-1} working capital ratio		Δ_{t-1} and Δ_{t-2} working capital ratio		Δ_{t-1} working capital ratio		Δ_{t-1} and Δ_{t-2} working capital ratio	
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE	DID	SE	DID	SE
Sales	t	0.0953***	(0.0218)	0.0541**	(0.0259)	0.0826***	(0.0201)	0.0762***	(0.0217)
	t+1	0.1380***	(0.0299)	0.0919***	(0.0333)	0.1652***	(0.0285)	0.1680***	(0.0344)
	t+2	0.1676***	(0.0348)	0.1245***	(0.0412)	0.2001***	(0.0351)	0.215***	(0.0424)
Labor	t	0.0523***	(0.0179)	0.0128	(0.0170)	0.0991***	(0.0158)	0.0939***	(0.0182)
	t+1	0.0804***	(0.0249)	0.0311	(0.0260)	0.1987***	(0.0240)	0.1848***	(0.0280)
	t+2	0.1126***	(0.0329)	0.0703**	(0.0353)	0.2454***	(0.0302)	0.2292***	(0.0351)
Capital	t	0.0673	(0.0414)	0.0487	(0.0453)	0.1634***	(0.0266)	0.1294***	(0.0261)
	t+1	0.1043*	(0.0617)	0.0981*	(0.0588)	0.22***	(0.0372)	0.2022***	(0.0397)
	t+2	0.1526**	(0.0698)	0.1677**	(0.0720)	0.2518***	(0.0478)	0.2523***	(0.0525)
TFP	t	0.0457**	(0.0264)	0.0398*	(0.0306)	-0.0137	(0.0195)	-0.0133	(0.0248)
	t+1	0.0618**	(0.0311)	0.0584*	(0.0369)	-0.0205	(0.0239)	-0.0045	(0.0289)
	t+2	0.0605*	(0.0311)	0.0525	(0.0369)	-0.0279	(0.0239)	0.0009	(0.0289)
N on (off) support		262	(6)	201	(7)	643	(2)	539	(2)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.19

Average effect of cross-border M&A on the acquirers' performance with different control groups – France.

		Specification C1		Specification C2		Specification C3	
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE	DID	SE
Sales	t	0.0708***	(0.0194)	0.0715***	(0.0202)	0.0766***	(0.0212)
	t+1	0.1039***	(0.0276)	0.1102***	(0.0267)	0.1252***	(0.0254)
	t+2	0.1090***	(0.0337)	0.1411***	(0.0333)	0.1582***	(0.0295)
Labor	t	0.0620***	(0.0131)	0.0222	(0.0178)	0.0482**	(0.0209)
	t+1	0.0707***	(0.0213)	0.0419	(0.0271)	0.0905***	(0.0212)
	t+2	0.1027***	(0.0254)	0.0781**	(0.0338)	0.1201***	(0.0268)
Capital	t	0.0420	(0.0346)	0.0181	(0.0501)	0.0538*	(0.0312)
	t+1	0.0863*	(0.0481)	0.0794	(0.0586)	0.1616***	(0.0471)
	t+2	0.1037	(0.0655)	0.1228*	(0.0726)	0.1884***	(0.0554)
TFP	t	0.0147	(0.0169)	0.0512***	(0.0164)	0.0315	(0.0196)
	t+1	0.0372*	(0.0223)	0.0688***	(0.0241)	0.0363	(0.0236)
	t+2	0.0137	(0.0278)	0.0656**	(0.0321)	0.0421	(0.0266)
N on (off) support		258	(12)	251	(19)	251	(19)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Specification C1: control group of firms without cross-border acquisition in t.

Specification C2: control group of firms without cross-border acquisition or national deal in t.

Specification C3: control group of firms without cross-border acquisition, national deal, or changes in the number of foreign subsidiaries in t.

Table 2.20

Average effect of cross-border M&A on the acquirers' performance with different control groups – United Kingdom.

		Specification C1		Specification C2		Specification C3	
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE	DID	SE
Sales	t	0.0789***	(0.0155)	0.1048***	(0.0174)	0.1213***	(0.0241)
	t+1	0.1443***	(0.0276)	0.2055***	(0.0283)	0.2190***	(0.0331)
	t+2	0.141***	(0.0347)	0.2348***	(0.0366)	0.2824***	(0.0443)
Labor	t	0.0924***	(0.0148)	0.1167***	(0.0170)	0.1008***	(0.0178)
	t+1	0.1538***	(0.0217)	0.2256***	(0.0236)	0.2108***	(0.0259)
	t+2	0.1749***	(0.0278)	0.2696***	(0.0312)	0.2489***	(0.0338)
Capital	t	0.1043***	(0.0270)	0.1700***	(0.0230)	0.1644***	(0.0316)
	t+1	0.1469***	(0.0339)	0.2324***	(0.0353)	0.2276***	(0.0469)
	t+2	0.1604***	(0.0427)	0.2806***	(0.0477)	0.2925***	(0.0577)
TFP	t	-0.0077	(0.0140)	-0.0071	(0.0152)	0.0234	(0.0212)
	t+1	0.0022	(0.0214)	-0.0041	(0.0216)	0.0224	(0.0273)
	t+2	-0.0201	(0.0257)	-0.0159	(0.0263)	0.0486	(0.0333)
N on (off) support		528	(8)	536	(10)	510	(10)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Specification C1: control group of firms without cross-border acquisition in t.

Specification C2: control group of firms without cross-border acquisition or national deal in t.

Specification C3: control group of firms without cross-border acquisition, national deal, or changes in the number of foreign subsidiaries in t.

Table 2.21
Rosenbaum bounds for the average effect of cross-border M&A on the acquirers' performance – France.

	Capital			Sales			Employment			TFP		
	t	t+1	t+2	t	t+1	t+2	t	t+1	t+2	t	t+1	t+2
1.0	***	***	***	***	***	***	***	***	***	**	***	
1.1	**	***	***	***	***	***	**	***	***		**	
1.2		**	**	***	***	***		**	**			
1.3				**	***	**						
1.4				**	***							
1.5					***							
1.6					**							
1.7					**							
1.8												
1.9												
2.0												

Standard errors, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.22
Rosenbaum bounds for the average effect of cross-border M&A on the acquirers' performance – United Kingdom.

	Capital			Sales			Employment			TFP		
	t	t+1	t+2	t	t+1	t+2	t	t+1	t+2	t	t+1	t+2
1.0	***	***	***	***	***	***	***	***	***			
1.1	***	***	***	***	***	***	***	***	***			
1.2	***	***	***	***	***	***	***	***	***			
1.3	***	***	***	***	***	***	***	***	***			
1.4	***	***	***	**	***	***	***	***	***			
1.5	***	***	***		***	***	***	***	***			
1.6	**	**	**		***	***	***	***	***			
1.7					***	**	***	***	***			
1.8					**	**	**	***	***			
1.9								***	***			
2.0								***	***			

Standard errors, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.23

Average effect of cross-border M&A on the acquirers' performance using alternative matching algorithms – France.

		Nearest Neighbor one nearest neighbor, caliper 0.1		Nearest Neighbor one nearest neighbor, radius 0.1		Nearest Neighbor three nearest neighbors		Mahalanobis (industry, time, age, and propensity score)	
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE	DID	SE	DID	SE
Sales	t	0.0815***	(0.0205)	0.0641***	(0.0169)	0.0847***	(0.0189)	0.0807***	(0.0305)
	t+1	0.1448***	(0.0292)	0.0914***	(0.0219)	0.1383***	(0.0247)	0.1223***	(0.0422)
	t+2	0.1275***	(0.0361)	0.0910***	(0.0254)	0.1335***	(0.0291)	0.1310***	(0.0482)
Labor	t	0.0408***	(0.0156)	0.0463***	(0.0132)	0.0373**	(0.0150)	0.0561***	(0.0214)
	t+1	0.0680***	(0.0240)	0.0603***	(0.0194)	0.0616***	(0.0218)	0.0869***	(0.0313)
	t+2	0.0769**	(0.0315)	0.0693***	(0.0235)	0.0762***	(0.0268)	0.1126***	(0.0412)
Capital	t	0.0870**	(0.0362)	0.0574**	(0.0291)	0.0643**	(0.0318)	0.0822*	(0.0458)
	t+1	0.1544***	(0.0520)	0.1039***	(0.0394)	0.1411***	(0.0436)	0.2011***	(0.0623)
	t+2	0.1654***	(0.0630)	0.1121**	(0.0474)	0.1546***	(0.0528)	0.2161***	(0.0765)
TFP	t	0.0405**	(0.0251)	0.0204	(0.0181)	0.0482***	(0.0211)	0.0269	(0.0327)
	t+1	0.0757***	(0.0317)	0.0325*	(0.0220)	0.0757***	(0.0256)	0.0338	(0.0373)
	t+2	0.0501	(0.0317)	0.0238	(0.0220)	0.0574**	(0.0256)	0.0195	(0.0373)
N on (off) support		259	(11)	264	(6)	264	(6)	159	(111)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.24

Average effect of cross-border M&A on the acquirers' performance using alternative matching algorithms – United Kingdom.

		Nearest Neighbor one nearest neighbor, caliper 0.1		Nearest Neighbor one nearest neighbor, radius 0.1		Nearest Neighbor three nearest neighbors		Mahalanobis (industry, time, age, and propensity score)	
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE	DID	SE	DID	SE
Sales	t	0.0945***	(0.0194)	0.0928***	(0.0146)	0.0919***	(0.0171)	0.0898***	(0.0236)
	t+1	0.1963***	(0.0296)	0.1791***	(0.0213)	0.1795***	(0.0254)	0.2146***	(0.0351)
	t+2	0.2361***	(0.0367)	0.2183***	(0.0255)	0.2203***	(0.0307)	0.2635***	(0.0425)
Labor	t	0.1049***	(0.0157)	0.1007***	(0.0118)	0.0996***	(0.0136)	0.0976***	(0.0194)
	t+1	0.1853***	(0.0237)	0.1907***	(0.0174)	0.1892***	(0.0205)	0.2041***	(0.0283)
	t+2	0.2318***	(0.0311)	0.2351***	(0.0222)	0.2280***	(0.0263)	0.2575***	(0.0367)
Capital	t	0.1448***	(0.0261)	0.1427***	(0.0197)	0.1467***	(0.0217)	0.1434***	(0.0309)
	t+1	0.1938***	(0.0373)	0.2009***	(0.0283)	0.2044***	(0.0323)	0.2387***	(0.0456)
	t+2	0.2605***	(0.0477)	0.2467***	(0.0353)	0.2593***	(0.0411)	0.3172***	(0.0570)
TFP	t	-0.0055	(0.0208)	-0.0034	(0.0157)	-0.0037	(0.0179)	-0.0039	(0.0251)
	t+1	0.0240	(0.0257)	0.0016	(0.0185)	0.0031	(0.0211)	0.0230	(0.0277)
	t+2	0.0193	(0.0257)	-0.0005	(0.0185)	0.0067	(0.0211)	0.0207	(0.0277)
N on (off) support		640	(6)	640	(6)	644	(2)	403	(243)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.25
Average effect of cross-border M&A on the acquirers' performance using alternative kernel functions – France.

		Kernel matching normal caliper 0.1		Kernel matching uniform caliper 0.1		Kernel matching epanechnikov bandwidth 0.2		Kernel matching epanechnikov bandwidth 0.02	
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE	DID	SE	DID	SE
Sales	t	0.0628***	(0.0168)	0.0652***	(0.0170)	0.063***	(0.0167)	0.0648***	(0.0175)
	t+1	0.0887***	(0.0218)	0.0949***	(0.0220)	0.0884***	(0.0216)	0.0931***	(0.0228)
	t+2	0.0878***	(0.0253)	0.0969***	(0.0256)	0.0866***	(0.0251)	0.0955***	(0.0267)
Labor	t	0.0450***	(0.0132)	0.0459***	(0.0133)	0.0449***	(0.0131)	0.0429***	(0.0138)
	t+1	0.0580***	(0.0193)	0.0618***	(0.0195)	0.0576***	(0.0192)	0.0566***	(0.0202)
	t+2	0.0665***	(0.0234)	0.0743***	(0.0237)	0.0658***	(0.0232)	0.0696***	(0.0246)
Capital	t	0.0542*	(0.0289)	0.0595**	(0.0293)	0.0542*	(0.0287)	0.0636**	(0.0305)
	t+1	0.0962**	(0.0392)	0.1055***	(0.0398)	0.0966**	(0.0388)	0.1244***	(0.0416)
	t+2	0.1035**	(0.0472)	0.1176**	(0.0479)	0.1038**	(0.0467)	0.1383***	(0.0502)
TFP	t	0.0204	(0.0180)	0.0217	(0.0183)	0.0208	(0.0179)	0.0236	(0.0190)
	t+1	0.0323*	(0.0219)	0.0345*	(0.0222)	0.0323*	(0.0217)	0.0360*	(0.0230)
	t+2	0.0236	(0.0219)	0.0250	(0.0222)	0.0230	(0.0217)	0.0262	(0.0230)
N on (off) support		264	(6)	264	(6)	264	(6)	264	(6)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.26

Average effect of cross-border M&A on the acquirers' performance using alternative kernel functions – United Kingdom.

		Kernel matching normal caliper 0.1		Kernel matching uniform caliper 0.1		Kernel matching epanechnikov bandwidth 0.2		Kernel matching epanechnikov bandwidth 0.02	
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE	DID	SE	DID	SE
Sales	t	0.0945***	(0.0194)	0.0928***	(0.0146)	0.0919***	(0.0171)	0.0898***	(0.0236)
	t+1	0.1777***	(0.0212)	0.1780***	(0.0215)	0.1781***	(0.0209)	0.1768***	(0.0221)
	t+2	0.2150***	(0.0254)	0.2189***	(0.0259)	0.2139***	(0.0250)	0.2199***	(0.0266)
Labor	t	0.1013***	(0.0117)	0.0996***	(0.0119)	0.1018***	(0.0115)	0.0977***	(0.0122)
	t+1	0.1909***	(0.0173)	0.1901***	(0.0176)	0.1913***	(0.0171)	0.1891***	(0.0181)
	t+2	0.2343***	(0.0221)	0.2345***	(0.0225)	0.2348***	(0.0217)	0.2359***	(0.0231)
Capital	t	0.1424***	(0.0196)	0.1439***	(0.0200)	0.1420***	(0.0192)	0.1477***	(0.0207)
	t+1	0.1975***	(0.0281)	0.2026***	(0.0287)	0.1969***	(0.0275)	0.2111***	(0.0298)
	t+2	0.2409***	(0.0351)	0.2511***	(0.0359)	0.2400***	(0.0344)	0.2658***	(0.0373)
TFP	t	-0.0039	(0.0156)	-0.0032	(0.0160)	-0.0037	(0.0153)	-0.0053	(0.0165)
	t+1	0.0003	(0.0184)	0.0009	(0.0188)	0.0004	(0.0180)	0.0000	(0.0194)
	t+2	-0.0026	(0.0184)	0.0003	(0.0188)	-0.0041	(0.0180)	-0.0009	(0.0194)
N on (off) support		644	(2)	644	(2)	644	(2)	644	(2)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.27

Average effect of cross-border M&A on the acquirers' performance using fixed effects estimation.

		France		United Kingdom	
$y_{t+s} - y_{t-1}$		DID	SE	DID	SE
Sales	t	0.0578**	(0.0256)	0.0884***	(0.0198)
	t+1	0.0610**	(0.0300)	0.1209***	(0.0255)
	t+2	0.0616*	(0.0344)	0.1358***	(0.0294)
Labor	t	0.0419**	(0.0180)	0.0721***	(0.0158)
	t+1	0.0305	(0.0201)	0.1233***	(0.0212)
	t+2	0.0279	(0.0269)	0.1374***	(0.0258)
Capital	t	0.0350	(0.0438)	0.1708***	(0.0310)
	t+1	0.0672	(0.0489)	0.1830***	(0.0390)
	t+2	0.0717	(0.0615)	0.2125***	(0.0429)
TFP	t	0.0195	(0.0233)	0.0147	(0.0154)
	t+1	0.0302	(0.0233)	0.0024	(0.0178)
	t+2	0.0327	(0.0251)	0.0032	(0.0192)
N		125,253		104,731	

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Results display the coefficients in a fixed effects regresison of the dependent variable in t, t+1, t+2 on a cross-border deal dummy variable.

Chapter 3

Productivity and the internationalization of firms: cross-border acquisitions versus greenfield investments

3.1 Introduction

This chapter adds to the empirical literature on the determinants of international activity at the firm level. In particular, it analyzes the sorting pattern of firms into different modes of foreign market entry depending on their productivity level with a focus on two different types of FDI, namely greenfield entry and cross-border mergers and acquisitions (M&A). The contribution of the present work is to test for the first time the productivity ranking of internationally active firms established in the theoretical model by Nocke & Yeaple (2007). The results show that FDI does not always involve the most productive firms within a sector as soon as it is accounted for the different modes of foreign investments. Thus, the analysis provides new empirical evidence on the Helpman et al. (2004) predictions that hold on average, but not across all types of FDI and not within all sectors. For productivity comparisons it matters whether MNEs engage abroad via greenfield investments or cross-border acquisitions.

Helpman et al. (2004) provide a model of heterogeneous firms in an industry that decide whether to serve the foreign market either through exports or to engage in FDI. Firms that want to build a foreign affiliate have to incur set-up costs that are higher than the fixed costs of exporting, but they save on per unit transportation costs. The implied proximity-concentration trade-off between producing closer to the consumer and producing with higher economies of scale leads to a specific productivity ranking of firms in an industry: only the most productive firms decide to invest abroad, while less efficient firms serve the foreign market via exports as illustrated schematically in figure 3.1. In this context, Helpman et al. (2004) refer to greenfield investments only, where a new firm is set-up abroad, while the alternative entry via cross-border acquisitions of existing firms is neglected (Neary, 2009).[1] More recently, the attention shifted to the composition of FDI with regard to the particular form of market entry. Different reasons arise for firms to choose either greenfield entry or cross-border acquisitions. Apart from strategic considerations – greenfield investments add a new firm to the foreign market, whereas an

[1] Furthermore, the primary motivation of firms to invest abroad is market access. This horizontal type of FDI refers to a duplication of the domestic production process abroad in order to serve the foreign market locally, thereby substituting exports (in the spirit of Markusen, 1984; Brainard, 1997). Vertical FDI, in contrast, transfers parts of the firm's production process into another country to exploit existing cross-country cost differences, thus resulting in increased intra-firm trade (such as analyzed in Helpman, 1984; Alfaro & Charlton, 2009).

acquisition can be thought of as a change in ownership (Markusen & Stähler, 2009; Görg, 2000) – one important difference is the acquisition of complementary assets.

This motive is well known in the M&A literature (see, for example, Jovanovic & Braguinsky, 2004), and empirical evidence shows that it is particularly relevant for cross-border acquisitions, while it plays a minor role for domestic deals (Frey & Hussinger, 2006). This is plausible if one thinks of parts of a firm's stock of knowledge to be market specific. The acquisition of a foreign target firm provides a way to gain access to these valuable assets and knowledge at the cost of the acquisition price. In contrast, MNEs choosing greenfield entry use their own technology both at home and abroad. Given this key difference in the nature of the two entry modes, the characteristics of firms engaging in either one can be expected to vary as well.

The latter distinction is picked up in the theoretical model of Nocke & Yeaple (2007) that analyzes the choice between three foreign entry modes: exporting, cross-border M&A, and greenfield investment.[2] Not only are firms modeled to be heterogeneous with respect to their productivity, but in addition sectors differ regarding the underlying source of the observed productivity differences. In one sector, firms display productivity differences mainly due to an internationally mobile capability, while more market-specific assets drive the heterogeneity of firms in the other industry. Depending on whether immobile or mobile capabilities determine firm heterogeneity within a certain industry, a different subset of firms decide to use a specific foreign entry mode. The known proximity-concentration trade-off still is at work in both types of industries so that more productive firms always prefer greenfield investment over exports. The group of firms that decides to acquire a foreign target firm, however, varies across the two types of industries. The interplay between the firms' capabilities, the importance of either capability in the sector, and the acquisition price that is set in the merger market determines whether the most or least productive firms of all internationally active firms engage in a cross-border acquisition.

The most efficient firms acquire an existing foreign firm whenever the underlying source of firm heterogeneity is easily transferred to foreign countries. Those firms seek to combine their own exceptional mobile assets with complementary foreign market-specific know-how to be able to exploit their productivity advan-

[2] Eicher & Kang (2005) also analyze these three entry modes, they focus on country and market characteristics and do not include firm heterogeneity.

tage abroad. The predicted productivity ranking implies the known sorting pattern of MNEs, exporters, and domestic firms, whereby those firms choosing greenfield investments are in between the productivity levels of acquirers and exporting firms. The described ranking is sketched in the second line of figure 3.1. If the relevant determinant of productivity advantages is less mobile across borders, however, the productivity ordering is partly reversed: in this case, firms with the lowest productivity of all internationally active firms acquire an existing foreign firm, while the most efficient firms engage in greenfield investments. For firms with the best immobile, more market-specific capabilities, it does not pay off to costly acquire the knowledge of the local firm as their productivity advantage is strong enough to compensate for its reduced effectiveness in the foreign market. The least productive firms, in contrast, need to acquire a foreign firm to be able to compete in the foreign market at all. In contrast to Helpman et al. (2004), FDI does not always involve the most productive firms if the entry mode is taken into account. The third line of figure 3.1 corresponds to this prediction.

Although the literature started to emphasize cross-border M&As and greenfield investments as two distinct modes of FDI recently (Nocke & Yeaple, 2008; Neary, 2009; Stiebale & Trax, 2011), empirical evidence is still rather scarce. Several empirical studies report a productivity advantage of established MNEs over exporters (Greenaway & Kneller, 2007; Tomiura, 2007; Arnold & Hussinger, 2010), with some evidence that large and more productive firms self-select to become MNEs (Girma et al., 2005; Jäckle & Wamser, 2010; Damijan et al., 2007). To the best of my knowledge there is no study that takes into account the two modes of FDI in addition to the firms' exporting decision with an explicit differentiation of mobile and non-mobile industries. Nocke & Yeaple (2008) find firms engaging in greenfield investments to be significantly more productive compared to acquirers in cross-border deals. However, exporting as a third mode of foreign market entry is not considered. In Raff et al. (2012), even more variations of possible entry modes are considered (wholly-owned versus jointly owned affiliates) analyzing a Japanese dataset. Without considering industry differences, the authors also find more productive firms to prefer greenfield investments over cross-border acquisitions.[3]

[3]There is more empirical work on the choice between greenfield investment and cross-border acquisitions such as Andersson & Svensson (1994). They usually focus on the influence of country and industry characteristics though and do not look at firm produc-

However, understanding which firms of an industry choose a certain foreign entry mode is important for several reasons. The effects of cross-border investments on the investing and competing firms probably depend on whether the most or less productive firms typically try to acquire a target firm abroad or plan to build up a new firm. Often discussed spillover effects of foreign entry, for example, might be contingent on the investors own productivity level (Keller, 2004; Javorcik, 2004). In addition, as shown by Nocke & Yeaple (2007), theoretical predictions regarding the effects of trade liberalization on average industry productivity and on production reallocations between firms crucially depend on the mapping from the firms' productivity to their internationalization choice. Finally, although cross-border investments are an even rarer firm activity than exporting, their relative impact across economies is huge (compare Bernard et al., 2007a): In 2007, the UNCTAD's (2010) World Investment Report counted 7,018 deals and 12,210 greenfield investments worldwide. At the same time, M&As were shown to be a potentially important channel for industry restructuring and asset reallocation after periods of trade liberalizations (Neary, 2007; Bertrand & Zitouna, 2006; Breinlich, 2008). In fact, transaction values involved in cross-border deals are extremely high: the total value of worldwide cross-border M&As amounted to over one trillion US dollars and accounted as such for over half of the value of global FDI flows at their latest peak in the year 2007.

Using a large firm-level panel data set of British firms, I am able to define the two types of foreign investment. The panel structure of the data allows to analyze productivity differences before the actual foreign market entry to separate the selection mechanism from the reverse effects of international activity on the firms' productivity. The distinction of the two industry types is operationalized using the share of intangible assets over non-financial fixed assets. I argue that industries with a high share of intangible assets can be interpreted as sectors where the firms' productivity advantage is based on mobile capabilities, as those intangibles can be combined with local assets in all parts of the firm simultaneously. Industries displaying a lower share are classified as non-mobile.

Considering acquirers of foreign firms and firms that build up a new affiliate abroad separately reveals considerable heterogeneity across modes of FDI and between industries. In line with the mechanism proposed by Nocke & Yeaple (2007), acquirers in cross-border deals are the most productive firms in sectors

tivity.

with a high share of intangibles, but they are the least productive group of all internationally active firms in the complementary low intangibles industry group. Not all future MNEs are necessarily more productive than exporters if the type of FDI and industry are taken into account. In contrast to the theoretical predictions, the specific source for the industries' high intangible assets seems to matter less, as cross-border acquirers are the most productive firms both in R&D and advertising-intensive manufacturing industries.

This chapter proceeds as follows: in the next section, I present the data and variable definitions, while section 3.3 discusses the empirical strategy. Section 3.4 contains the results. Section 3.5 is devoted to several robustness checks, the last section concludes this chapter.

3.2 Data

The analysis is based on a comprehensive firm-level data set that is constructed combining financial data and ownership information for European firms with a global M&A database that allows for the distinction between the two modes of foreign direct investment.

The financial data is taken from the Amadeus database published by Bureau van Dijk, which provides information on firms' balance sheets, and profit and loss accounts for up to ten years. The data is collected from company reports that are supplemented by specialized regional information providers. These data have been used in numerous studies on FDI such as in Egger et al. (2010); Helpman et al. (2004); Budd et al. (2005). Among the main advantages of the dataset are its extensive coverage as it is not limited to listed companies. Although there is some bias towards larger firms, this should not be problematic for the present analysis as the smallest firms are typically not involved in international activities. A fundamental feature of the data is the availability of unconsolidated accounts that display balance sheet items separately for the single enterprise in contrast to the whole corporate group. Combining eight consecutive updates of the Amadeus database for the years 2000-2007, I have yearly data on the number of foreign subsidiaries of each firm.[4] I merge the observations from Amadeus with the transaction data from

[4]Each update of Amadeus provides information on subsidiaries for one point in time only.

the Zephyr database, an M&A database from the same provider. Zephyr includes data on M&As, IPOs, joint ventures, and private equity transactions and provides information about date and value of a deal, as well as identifiers for the firms involved in the deal.

The data structure of this new combined European firm level data set allows for the necessary differentiation between cross-border M&As and greenfield investments and the reconstruction of the growing international commitment of firms over time. The exact number of cross-border deals is extracted from the Zephyr data. The information for greenfield projects has to be approximated: Subtracting the number of cross-border deals per year and firm from the change in the reported number of foreign subsidiaries between two years given in the Amadeus data, I define greenfield investments as a residual category. I concentrate on investments where the acquirer gains at least a majority interest in the target firm as it is usual in the M&A literature.[5]

The approximation of greenfield investments suffers from two potential inaccuracies. Although the quality of the M&A database is high, for some deals not all necessary information is reported. In those cases, the generated value for greenfield investment would be too high when the resulting affiliate is reported in Amadeus. This should be a minor problem, however, as the two datasets origin from the same data provider, so that all relevant data for the deal should be available if the affiliate is reported in Amadeus.[6] The figures on greenfield investments are downward biased, on the other hand, whenever a firm closes or sells previously acquired firms within one year. If these measurement errors would be too strong, they could blur the classification of the two types of investment. The observed difference in the productivity levels should then be biased if anything towards zero. As the productivity ranking changes across sectors mainly due to the group of cross-border acquirers, the main results should not be affected by this approximation error.

The main variable of interest is the firms' efficiency. In line with the empirical literature, a frequently used measure of a firm's productivity level is the total factor

[5]Most deals are majority acquisitions or even full acquisitions. The remaining small part of deals results from share buyback activities involving increases in the stake hold of only few percentage points.

[6]When comparing aggregate statistics derived from own calculations of the Zephyr database restricted to deals with a deal value above 10 million US$ with those from Thompson financial data as used in Brakman et al. (2007a), the coverage of transactions appears to be very similar.

productivity (TFP) calculated as the residual of a production function estimation. I implement Olley & Pakes' (1996) estimation algorithm that uses investments to control for unobserved productivity shocks that induce a simultaneity problem in the TFP estimation and that also controls for firm exit.[7] I calculate TFP for all observations with sales, labor, and capital figures available. As in the theoretical literature efficiency is usually expressed directly in terms of sales, this measure and alternative productivity estimates are discussed in the robustness section.

Next, I define exporters in a comparable way to cross-border acquisition and greenfield investment measures. Thinking about FDI, a crucial distinction is between the stock or flow of FDI. The former is the amount already invested abroad, while the latter refers to the change in the stock of FDI. Cross-border M&As and greenfield investments can be interpreted as flow variables as they reflect additional investment abroad, whereas the number of foreign affiliates corresponds to the stock of FDI. As no information on exports per market is available in the dataset, I generate a variable that is equal to one if a firm increases significantly its export turnover (export turnover grows more than 50%). While this approach might have its weaknesses regarding the direct link to the theoretical underpinnings, it is in line with the empirical literature that tested Helpman et al. (2004). To the best of my knowledge there is no dataset available that combines the necessary panel firm level information on exporting with the distinction of the two types of foreign direct investments.

For the estimation sample, British firms are selected, as the data availability is particularly high and the United Kingdom is one of the countries worldwide with the most acquirers in cross-border deals (Brakman et al., 2007a). Only firms for which unconsolidated balance sheet data are available are included. Firms that are active in the primary sector, holding companies (NACE code 7415), and firms from the public sector (NACE 75, 91) are deleted. I exclude financial companies (NACE 65-67) as the definition of output or sales and hence any measure of total factor productivity is not comparable to other firms. Inspecting the growth rates of variables like firm size and number of employees, I delete large outliers at both ends of the distribution as they could indicate an unreported merger. After applying standard cleaning procedures,[8] I am left with 249,014 firm-year observations.

[7]The alternative estimation strategy using material inputs instead of investments as suggested in Levinsohn & Petrin (2003) is not an option as this variable is not available for the UK.

[8]Deletion of observations with implausible values such as negative input factors or

3.3 Estimation

There are two commonly used approaches to measure the productivity differences between firms. One strategy is to test for differences in the productivity distributions between groups of firms in the spirit of Delgado et al. (2002) and Girma et al. (2005), the other consists of regressing a productivity measure on internationalization dummies as in Bernard & Jensen (1999) and Head & Ries (2003). Following the latter approach, I estimate the following equation separately for each industry:

$$\begin{aligned} ln(\text{TFP}_{it}) = \alpha_0 + \alpha_X futureX_{it} + \alpha_{CB} futureCB_{it} + \alpha_{GI} futureGI_{it} \\ + \beta_X X_{it} + \beta_{CB} CB_{it} + \beta_{GI} GI_{it} + \boldsymbol{\beta C_{it}} + \gamma_j + \gamma_t + \varepsilon_{it}, \end{aligned} \quad (3.1)$$

where X refers to exporters, CB to acquirers in a cross-border deal and GI to firms engaged in greenfield investment. Theses variables define firms who have already used the respective entry mode within the last three years. In combination with the prefix 'future', the variables refer to firms that currently do not but that are going to use the specific entry mode within the next three years. Including these two sets of variables allows to separate the ex-ante productivity differential before the actual foreign market entry that reflects the selection mechanism of interest from potential productivity effects after the firm has entered the foreign market. The estimated coefficients α_k of the internationalization dummies reflect the productivity advantage of the group of firms that is going to choose the respective internationalization strategy compared to firms that will not use the respective entry mode given other international activities, which is the focus of this contribution. To see whether firms of group k are more or less productive than firms in group l, two-sided t-tests of the following null hypothesis are performed:

$$H_0 : \alpha_l - \alpha_k = 0, \quad (3.2)$$

where α_k and α_l are the estimated coefficients and $k, l \in \{X, CB, GI\}$.

C_{it} is a standard set of control variables to capture further systematic differences that might bias the estimated productivity gap (Wagner, 2007). The log of the number of employees as well as its square and the firms' capital stock are included as measures of firm size, the log average wage accounts for the composi-

intangible assets ratios above one, and with growth rates larger than the highest and smaller than the first 200-quantile.

tion of the labor force, and the age of a firm and its square are included to reflect learning effects. In addition, I control for foreign majority shareholders as foreign owned firms usually have a productivity advantage over domestically owned firms (Harris & Robinson, 2003); a further dummy identifies public companies (Harhoff et al., 1998). γ_j refers to a set of industry dummies at the two-digit NACE level, as productivity comparisons are meaningful only within industries, and they capture industry characteristics that could influence the entry mode choice. γ_t stands for a set of time dummies to account for macroeconomic circumstances. Given the panel structure of the model, standard errors are clustered at the firm level to correct for intra-group correlated standard errors.

The chosen approach is clearly descriptive in nature and does not claim a causal interpretation. In the literature that compares exporters with non-exporters, several estimation methods for the identification of productivity as a causal factor have been applied that could be extended in principle to include MNEs.[9] The main difficulty of such alternative approaches like, for instance, a multinomial choice model, lies in the construction of mutually exclusive categories of firms according to their internationalization status. Considering all possible combinations, six categories had to be included when introducing the two types of FDI.[10] The number of observations in some industries for some of these categories is too low to achieve stable estimates. In addition, another advantage of the chosen regression framework is the possibility to control for all potential combinations of past international experience and the various internationalization patterns. Thus, I can analyze the selection of firms into the respective internationalization modes without restricting the analysis to future international and current domestic firms. The results of Andersson & Svensson (1994), for example, indicate that the probability to choose a certain FDI mode might depend on the existing international experience of the firm. A restricted sample would probably be highly selective and additionally reduce the number of observations of future cross-border acquisitions and greenfield investments drastically.

[9] An example from the exporting literature is Bernard & Jensen (2004), who derive an estimable equation of the export decision including past export status and firm fixed effects in order to account for entry costs of exporting and unobserved heterogeneity.

[10] The categories would be: domestic firms, exporters only, exporters and cross-border acquirers, exporters and firms engaged abroad via greenfield investments, firms without exports, but with both types of FDI, and finally firms that choose all three modes of foreign market entry.

The next step consists in finding an appropriate industry classification that defines industries with mobile and non-mobile capabilities. Nocke & Yeaple (2007) themselves provide concrete examples for the concept of mobile and immobile capabilities that determine the different selection patterns across industries. Marketing expertise is of less value abroad as market conditions differ and existing relationships to market participants provide an advantage in the home market only. Such knowledge thus can be interpreted as immobile across countries. A firm's production technology, on the other hand, can be transferred relatively easily across borders without losing its effectiveness. The operationalization of these capabilities is not straightforward, though.

The balance sheet data at hand is not detailed enough to include marketing expenditure or a similar measure for the importance of immobile capabilities nor does it include a direct measure of firms' R&D efforts or R&D output. Searching for industry data from other sources, it appears to be difficult to find data at the appropriately detailed level for all industries on both dimensions.

Therefore, I suggest a different measure for mobile capabilities that is directly observable in the data, which is the share of intangible assets relative to the firm's non-financial fixed assets. At first sight, this does not seem to be a direct implementation of the theoretical distinction. Nocke & Yeaple (2007) clearly describe that intangible assets determine the heterogeneity between firms, but they want to stress the different types of intangible assets. According to international accounting standards patents, licenses, and computer software are listed as intangible assets, but also customer lists and supplier relationships. However, as the most important feature that distinguishes the firms' different assets is whether they can easily be transfered to another firm, intangible assets might capture this distinction quite well as they form exactly that part of firms' assets that can be employed simultaneously in more than one location. Combined with the foreign market-specific assets of the target firm, the described complementarities can be exploited.

Hence, I rank the two-digit NACE industries according to their mean intangible assets ratio. The top quartile of all industries is labeled 'High intangibles industry'. The resulting industry should correspond to the sector with mobile capabilities. The complementary category 'Low intangibles industry' subsumes the rest of all industries, as a proxy for the sector in which non-mobile capabilities are the relevant source of heterogeneity in the firms' productivity. Manufacturing of tobacco products, and research and development (NACE 16 and 73) are examples from the manufacturing and service sector, respectively, for the former. Manufacturing of plastic products or real estate activities (NACE 21 and 70), for instance, belong to the low-intangibles group. The list of industries in the two categories is given in table 3.1. Alternative industry classifications are considered as robustness checks in section 3.5.

3.4 Results

Before looking at the results of the regression analysis, some descriptive facts are presented. Table 3.2 displays the share of firms with different internationalization statuses. Note that some firms may be included in more than one category. In the dataset, 11.6% of all British firms in the sample export. This is higher compared to numbers found for the U.S. (4% of all firms, compare Bernard et al., 2007a). This reflects the coverage of the dataset, which is very comprehensive for larger firms, while the smallest firms that are less likely to export are somewhat under-represented. The shares considering manufacturing firms only or excluding small firms are even higher (37.4%) and similar to other studies for the U.K., illustrating the importance of data selection (Girma et al., 2004, for example, report a share of 35%). The share of MNEs is considerably smaller with only 1.9% of all firms and less than 5% even for large firms in the manufacturing industry. Finally, the shares of cross-border acquirers and firms that engage in greenfield investment are shown. These shares are less than one percent of all firms with even less acquirers than greenfield investors.[11]

Table 3.3 provides unconditional means of some firm characteristics in the estimation sample for the year 2006.[12] Domestic firms are smaller than future exporters and those in turn are smaller than future MNEs, both in terms of sales and employment. The difference between the two types of FDI firms is not very pronounced. On average, exporters are also less productive than both cross-border acquirers and firms engaged abroad via greenfield investments. Interestingly, firms that have acquired a foreign target display the highest average share of intangible investments, possibly indicating a complementary-asset seeking motive.

[11]Note that the numbers for the last two categories do not add up to the share of MNEs measured as a stock variable illustrating the importance of the distinction between the stock and flow of FDI.

[12]The total numbers of observations in the sample are 10,939, 393, and 3,183 for future exporters, acquirers and greenfield firms, respectively.

The estimation results are presented in table 3.4. The estimated coefficients of equation 3.1 are shown in the upper panel separately for the low and high intangibles sector, while the statistics of the tests on equality of the coefficients are displayed below. In the regression for low intangibles industries, future exporting firms display a medium productivity advantage of 7,2%. For greenfield investors, the highest coefficient shows up (13,1%). The cross-border acquirer coefficient is close to zero and not significant at any reasonable level. The productivity differences between groups are not statistically significant, though, due to the high standard error of the cross-border dummy, for which the number of ones is low. For the high intangibles sample, contrasting results can be observed. Here, the group of future cross-border acquirers has the highest and the only statistically significant coefficient (44,3%), while the other two entry modes are not related to a notable productivity advantage. The difference between exporters and greenfield investors is again not significantly different from zero, but the null hypotheses of equality of coefficients for the comparisons with cross-border acquirers can be rejected at the 1% level. The results are in line with the predictions of Nocke & Yeaple (2007), as the high intangibles sector corresponds to the industry in which the firms' heterogeneity is based on mobile capabilities, where the most efficient firms seek to aquire complementary assets abroad. The heterogeneity that shows up in the results is hidden in studies ignoring industry differences and the composition of FDI.

Figure 3.2 visualizes the productivity differences. The upper graph shows the cumulative density functions of the firms' productivity levels separately for each internationalization mode in the low intangibles sector, the second graph refers to the high intangibles industry. Here, I do not control for simultaneous use of more than one entry mode. Without testing formally for stochastic dominance, inspecting the location of the productivity distributions of the various entry modes gives a more complete picture of the productivity differences as a ranking of the complete distributions is established. The productivity distributions of exporters and greenfield investors is located clearly to the right of the domestic firms' line in both pictures, while the productivity distribution of the two modes is very close to each other. The distribution for cross-border acquirers in the low intangible industries is close to the distribution of exporters and greenfield investors and some quantiles are almost the same as the corresponding values for domestic firms. This finding illustrates why no significant productivity advantage of cross-border acquirers could be found in the corresponding regression analysis. In the high intangibles sector, in contrast, the productivity distribution of cross-border acquirers clearly dominates all other distributions. In addition to the mean, every quantile of the cross-border acquirers' productivity distribution is the largest compared to the rest of the firms in the sample. The high coefficient in the regression approach seems not to arise due to influential observations but rather reflects systematically higher productivity levels of cross-border acquirers in the mobile capabilities industry.

An important issue for the discussion is whether the results are sensitive towards the specific sample or measurement. For this discussion it appears to be helpful to provide comparable results with previous empirical work.

Table 3.5 therefore shows estimation results if the heterogeneity of FDI modes and industries is neglected. Future MNEs are defined as firms that are going to acquire an additional affiliate in the upcoming three years. The results are similar to the existing literature, as future exporters are more productive than domestic firms, and future MNEs display even higher productivity levels (compare Arnold & Hussinger, 2010; Girma et al., 2004, for example). The difference between the estimated coefficients is significant at the 10% level. The known result that the most productive firms become MNEs thus holds on average, but hides considerable heterogeneity in the relation between a firm's productivity and its mode of foreign entry.

3.5 Robustness checks

In the estimations presented so far, a vector of control variables was always included to filter out the pure productivity differences. To show that none of the included firm characteristics has a strong enough influence to wipe out the observed ranking, I estimate the raw productivity differences between the groups. Therefore, only the post-entry dummies together with time and industry dummies, but no controls for further firm characteristics are included in table 3.6. The estimated coefficients turn out to be larger in size, but the productivity ranking itself does not change. All firms active in international markets turn out to be significantly more productive compared to their domestic counterparts, but partly only due to their size, skill structure, and age. The productivity ranking of the groups of international firms using different entry modes is not affected though.

Further, as the theoretical model strictly speaking refers to domestically owned firms only, table 3.7 displays the results excluding firms with a majority foreign shareholder. The estimations are again quite similar to the first set of results. While foreign owned firms are known to be more productive, this advantage seems not to be systematically related to the sorting of firms into different internationalization strategies.

Apart from the change in the estimation sample, I consider some changes in the variable definitions. As described in the data section, the Olley & Pakes method used to construct a consistent TFP measure takes care of some of the major estimation problems, nevertheless it critically hinges on functional form restrictions and instrument variables. Therefore, I also use labor productivity (total sales per employee) as an alternative productivity measure (table 3.8), the residuals from a simple OLS estimation of a Cobb-Douglas type production function (table 3.9), and estimates including firm fixed effects (table 3.10).[13] For these variations, I do not include control variables as the results would be identical conditioning on labor and capital input. The correlation between the various measures is always higher than 0.9, thus causing no significant change in the described results. The only exception is the latter version, where cross-border acquirers have a higher coefficient than exporters in the low intangible industry, however, the difference is not statistically significant.

For reasons of comparability, in the baseline specification the exporter variable is equal to one if the share of turnover resulting from export activities increased significantly. Table 3.11 recalculates the results for the usual stock definition. That is, the exporter dummy equals one for firms that are going to export and zero otherwise. The coefficients and test statistics again almost do not change.

The next variations refer to alternatives to the chosen industry classification. To check the sensitivity of the results towards the grouping of the industries (top-quartile), I perform regressions that include all industries and I interact all foreign entry dummy variables with the mean industry share of intangibles.

$$\begin{aligned} ln(\text{TFP}_{it}) &= \beta_0 + \beta_X X_{it} + \beta_{CB} CB_{it} + \beta_{GI} GI_{it} + \beta_{m_X} X_{it} * m_j \\ &+ \beta_{m_{CB}} CB_{it} * m_j + \beta_{m_{GI}} GI_{it} * m_j + \boldsymbol{\beta C_{it}} + \gamma_j + \gamma_t + \epsilon_{it} \end{aligned} \quad (3.3)$$

where m_j is the mean share of intangible assets relative to non-financial fixed assets in a two-digit NACE industry. In this estimation, the interaction between cross-border acquisitions and the mean ratio of intangible assets should have a

[13]Another measure would be value added per employee; unfortunately, value added is rarely reported for British firms.

positive coefficient, while the interaction terms with greenfield investments and exporters are expected to be insignificant. Table 3.12 gives the respective estimates. The coefficients on the pre-entry dummies are positive and significant for future exporters and greenfield investors, while cross-border acquisitions are related to a lower productivity. Looking at the interaction terms, however, the only positive, large, and significant effect is found for cross-border acquirers in line with expectations. To interpret the results in a meaningful way, the lowest and highest values for the mean share of intangibles have to be considered to get the possible range of the effect. The lowest intangibles ratio is 1.3%, while the sector with the highest value reaches 11.2%. This results in a combined effect between -0.245 and 0.578, implying cross-border acquirers to be the least productive firms in low intangibles industries, but they are the most productive firms in industries with high intangibles. This alternative specification thus again confirms the theoretical predictions.

As a further robustness check, I consider manufacturing firms separately from the service industries. As for many services a more direct customer-producer interaction is necessary, the relevant knowledge and technology in this sector might be less mobile across borders than in manufacturing industries. Thus I expect the results for the manufacturing to be similar to those in the mobile industry, whereas the service sector should display similar patterns as the non-mobile sector. Table 3.13 gives the results for this alternative classification. The results are in line with expectations, as in the manufacturing sector, the coefficients resemble the high intangibles industry results except that exporters display a significant productivity advantage in this case. The estimates of the service industries correspond to the industry where less mobile capabilities dominate. None of the t-tests on the pairwise equality of the coefficients can be rejected, though.

Finally, I also use data on R&D and advertising intensity to explicitly take into account the suggestions by Nocke & Yeaple (2007). I use the data from Peneder (2002), who presents figures for industry R&D and advertising expenditures over sales for the US economy at the three-digit NACE level, based on the assumption that the US economy serves as a useful point of reference for its technological leadership.[14] This comes at the cost of restricting the sample to the manufacturing sector only. The results for industries classified into those with low and high

[14] Data on R&D intensities for UK industries would be available, I do not find information for the UK on the advertising intensities of the same industry classification.

R&D and advertising ratios are shown in table 3.14 and 3.15, respectively.[15] The acquirers display the largest and significant coefficient both in the 'High R&D intensity' and 'High advertising intensity' estimation, while the respective coefficient is rather close to zero and not significant at any reasonable level in the remaining columns. Thus, at least for manufacturing industries, the distinction of the underlying type of intangible asset seems to be less relevant. The classification referring to the importance of intangible assets seems to be robust towards a finer differentiation. As intangible assets can be transfered and employed at different firms at the same time, they appear to be a good operationalization of the concept of mobile capabilities.

[15] A simultaneous classification into high advertising/low R&D and high R&D/low advertising is not possible, as the low number of ones for cross-border deals does not lead to any significant results.

3.6 Conclusion

In this chapter, the empirical literature on the determinants of international activity at the firm level is extended towards different modes of FDI. While several empirical studies confirm a productivity ranking based on Helpman et al. (2004), this contribution shows that these results hold only on average for all types of FDI and over all industries. In line with Nocke & Yeaple (2007), it matters whether MNEs engage abroad via greenfield investments or cross-border acquisitions. Splitting MNEs into acquirers of foreign firms and firms that build a new firm abroad reveals that in the U.K., acquirers in a cross-border deal are the most productive firms in industries where intangible assets are high relative to non-financial fixed assets, but they are the least productive group of all international active firms in the complementary low intangibles industry group. Exporters and firms engaging in greenfield investments display a productivity advantage over domestic firms of similar size in both industries. Whether the higher intangibles stem from higher R&D efforts or from higher marketing expenses seems not to be of primary importance, at least for manufacturing industries. It is shown that these results are not an artifact of the specific dataset as results comparable to the existing literature on MNEs can be produced. It should be taken into account that the motives for firms choosing different internationalization forms potentially differ across industries and thus the effects of trade liberalization might vary across industries as well.

3.7 Tables

Figure 3.1
Schema of the productivity ranking.

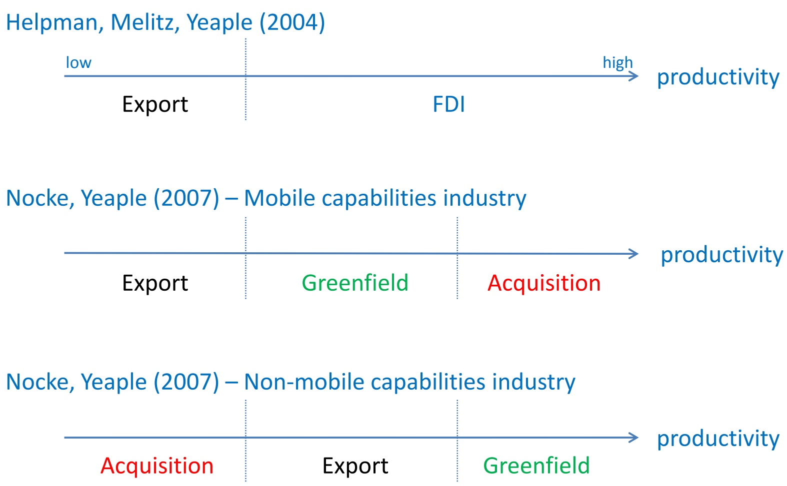

Table 3.1
Examples for the industry classification.

	Low intangibles industries
17	Manuf. of textiles
21	Manuf. of pulp, paper and paper products
25	Manuf. of rubber and plastic products
51	Wholesale trade and commission trade
60	Land transport; transport via pipelines
70	Real estate activities
	High intangibles industries
16	Manuf. of tobacco products
22	Publishing, printing and reproduction of recorded media
24	Manuf. of chemicals, chemical products and man-made fibres
33	Manuf. of medical, precision and optical instruments, watches and clocks
52	Retail trade
73	Research and Development

The complete list of two-digit NACE codes of the high intangibles category: 16, 22, 23, 24, 90, 33, 34, 41, 52, 55, 73. The remaining industries fall in the low intangibles category.

Table 3.2
Share of firms according to their internationalization status in 2006 (in %).

Exporters	
All firms	11.6
Manufacturing firms	32.6
Firms > 10 employees	17.2
Manufacturing firms > 10 employees	37.4
MNEs (stock of foreign affiliates)	
All firms	1.9
Manufacturing firms	4.1
Firms > 10 employees	2.7
Manufacturing firms > 10 employees	4.4
Cross-border acquirers	
All firms	0.09
Manufacturing firms	0.11
Firms with more than 10 employees	0.12
Manufacturing firms > 10 employees	0.12
Greenfield investors	
All firms	0.7
Manufacturing firms	1.6
Firms with more than 10 employees	1.0
Manufacturing firms > 10 employees	1.7

Table 3.3
Descriptive statistics of the different firm groups in 2006.

	Domestic firms	Exporters	Cross-border acquirers	Greenfield investors
United Kingdom				
Log sales	7.867	9.200	10.620	10.384
Log employment	3.045	3.857	5.179	4.81
Log TFP	0.826	1.455	1.722	1.804
Share of intangibles	0.051	0.094	0.222	0.143
N (firm-year observations)	174,275	379	30	268

Unconditional means. Calculations are based on the three years before entering the respective status via the respective internationalization mode. TFP: Olley & Pakes (1996) algorithm. Share of intangibles: intangible assets over non-financial fixed assets.

Table 3.4
Considering heterogeneity across modes of FDI and industries –
Classification: industry share of intangible assets.

	Low intangibles	High intangibles
Estimated coefficients		
Future export expanding firm	0.072***	-0.003
	(0.012)	(0.032)
Future cross-border acquirer	0.003	0.443***
	(0.073)	(0.118)
Future greenfield investor	0.131***	0.001
	(0.025)	(0.044)
Test of equality of coefficients		
Future exporter = Future acquirer	0.069	-0.446***
	(0.075)	(0.121)
Future exporter = Future greenfield	-0.059**	-0.004
	(0.027)	(0.056)
Future acquirer = Future greenfield	-0.128	0.442***
	(0.079)	(0.123)
Past international activity	Yes	Yes
Control variables	Yes	Yes
Industry and time effects	Yes	Yes
N	212,767	36,247
adjusted R^2	0.467	0.553

Coefficients from an OLS regression with Olley & Pakes log TFP as the dependent variable (estimated standard errors in parentheses). ***, **, * denote significance levels 1, 5, 10%, respectively. Control variables: log number of employees, log number of employees squared, log average wage, log age, squared log age, foreign majority shareholder dummy, legal form dummy, log capital stock, exporter, post-cross-border deal and post-greenfield investment dummies, and a set of time and two-digit NACE industry dummies. Standard errors in parentheses. Two-sided t-test with null hypothesis pre-exporting dummy coefficient is equal to pre-cross-border dummy coefficient, pre-exporting dummy coefficient is equal to pre-greenfield investment dummy coefficient, and pre-cross-border dummy coefficient is equal to pre-greenfield investment dummy coefficient. Sectors are classified according to their mean share of intangible assets over non-financial fixed assets. High intangibles industries are the top quartile of all industries ranked by their respective mean share.

Figure 3.2
Cumulative distribution functions of the firms' productivity
by foreign entry mode and industry.

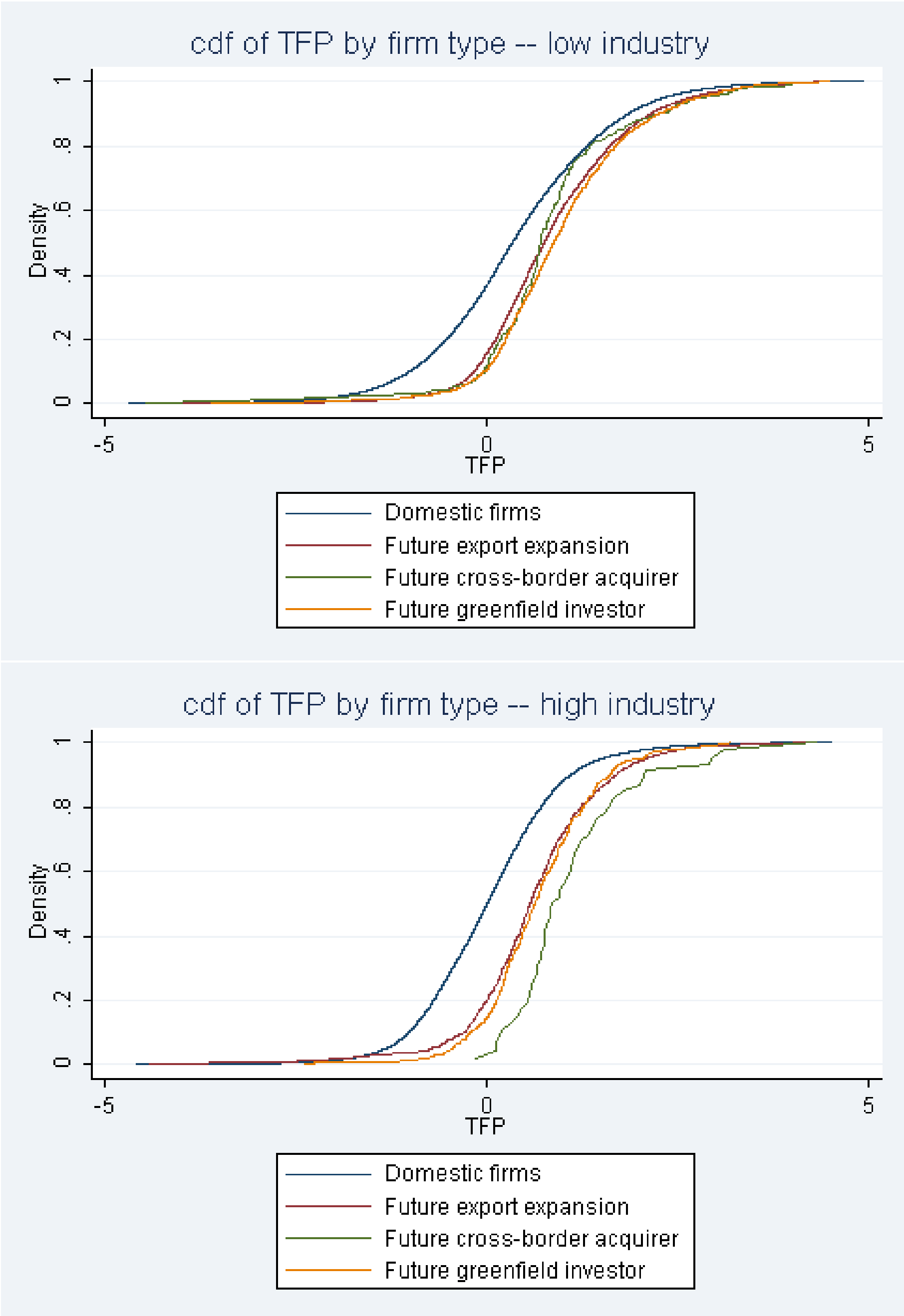

Table 3.5
Ignoring heterogeneity.

Estimated coefficients	
Future exporting firm	0.063***
	(0.011)
Future MNE	0.107***
	(0.022)
Test of equality of coefficients	
Future exporter = Future MNE	-0.044*
	(0.025)
Past international activity	Yes
Control variables	Yes
Industry and time effects	Yes
N	249,014
adjusted R^2	0.478

Coefficients from an OLS regression with Olley & Pakes log TFP as the dependent variable (estimated standard errors in parentheses). ***, **, * denote significance levels 1, 5, 10%, respectively. Control variables: log number of employees, log number of employees squared, log average wage, log age, squared log age, foreign majority shareholder dummy, legal form dummy, log capital stock, exporter and MNE dummies, and a set of time and two-digit NACE industry dummies. Standard errors in parentheses. Two-sided t-test with null hypothesis pre-exporting dummy coefficient is equal to pre-FDI dummy coefficient.

Table 3.6
Considering heterogeneity across modes of FDI and industries –
Only controlling for year and industry.

	Low intangibles	High intangibles
Estimated coefficients		
Future export expanding firm	0.292***	0.106***
	(0.013)	(0.036)
Future cross-border acquirer	0.287***	0.671***
	(0.085)	(0.147)
Future greenfield investor	0.459***	0.291***
	(0.028)	(0.053)
Test of equality of coefficients		
Future exporter = Future acquirer	0.005	-0.565***
	(0.086)	(0.150)
Future exporter = Future greenfield	-0.167***	-0.185***
	(0.031)	(0.066)
Future acquirer = Future greenfield	-0.172*	0.380**
	(0.090)	(0.158)
Past international activity	Yes	Yes
Control variables	No	No
Industry and time effects	Yes	Yes
N	212,767	36,247
adjusted R^2	0.184	0.261

Coefficients from an OLS regression with Olley & Pakes log TFP as the dependent variable (estimated standard errors in parentheses). ***, **, * denote significance levels 1, 5, 10%, respectively. Control variables: exporter, post-cross-border deal and post-greenfield investment dummies, and a set of time and two-digit NACE industry dummies. Standard errors in parentheses. Two-sided t-test with null hypothesis pre-exporting dummy coefficient is equal to pre-cross-border dummy coefficient, pre-exporting dummy coefficient is equal to pre-greenfield investment dummy coefficient, and pre-cross-border dummy coefficient is equal to pre-greenfield investment dummy coefficient.

Table 3.7
Considering heterogeneity across modes of FDI and industries – Only domestic firms.

	Low intangibles	High intangibles
Estimated coefficients		
Future export expanding firm	0.073***	-0.023
	(0.013)	(0.040)
Future cross-border acquirer	0.010	0.380***
	(0.076)	(0.115)
Future greenfield investor	0.142***	0.010
	(0.028)	(0.051)
Test of equality of coefficients		
Future exporter = Future acquirer	0.062	-0.403***
	(0.078)	(0.122)
Future exporter = Future greenfield	-0.069**	-0.033
	(0.031)	(0.067)
Future acquirer = Future greenfield	-0.132	0.370***
	(0.083)	(0.123)
Past international activity	Yes	Yes
Control variables	Yes	Yes
Industry and time effects	Yes	Yes
N	181,298	31,278
adjusted R^2	0.472	0.545

Coefficients from an OLS regression with Olley & Pakes log TFP as the dependent variable (estimated standard errors in parentheses). ***, **, * denote significance levels 1, 5, 10%, respectively. Control variables: log number of employees, log number of employees squared, log average wage, log age, squared log age, foreign majority shareholder dummy, legal form dummy, log capital stock, exporter, post-cross-border deal and post-greenfield investment dummies, and a set of time and two-digit NACE industry dummies. Standard errors in parentheses. Two-sided t-test with null hypothesis pre-exporting dummy coefficient is equal to pre-cross-border dummy coefficient, pre-exporting dummy coefficient is equal to pre-greenfield investment dummy coefficient, and pre-cross-border dummy coefficient is equal to pre-greenfield investment dummy coefficient. Sample excluding firms with a foreign majority shareholder.

Table 3.8
Considering heterogeneity across modes of FDI and industries – Labor productivity.

	Low intangibles	High intangibles
Estimated coefficients		
Future export expanding firm	0.240***	0.093**
	(0.013)	(0.037)
Future cross-border acquirer	0.161*	0.581***
	(0.083)	(0.153)
Future greenfield investor	0.313***	0.118**
	(0.027)	(0.051)
Test of equality of coefficients		
Future exporter = Future acquirer	0.078	-0.488***
	(0.084)	(0.155)
Future exporter = Future greenfield	-0.074**	-0.025
	(0.031)	(0.064)
Future acquirer = Future greenfield	-0.152*	0.463***
	(0.089)	(0.162)
Past international activity	Yes	Yes
Control variables	Yes	Yes
Industry and time effects	Yes	Yes
N	212,767	36,247
adjusted R^2	0.174	0.259

Coefficients from an OLS regression with log labor productivity as the dependent variable (estimated standard errors in parentheses). ***, **, * denote significance levels 1, 5, 10%, respectively. Control variables: log number of employees, log number of employees squared, log average wage, log age, squared log age, foreign majority shareholder dummy, legal form dummy, log capital stock, exporter, post-cross-border deal and post-greenfield investment dummies, and a set of time and two-digit NACE industry dummies. Standard errors in parentheses. Two-sided t-test with null hypothesis pre-exporting dummy coefficient is equal to pre-cross-border dummy coefficient, pre-exporting dummy coefficient is equal to pre-greenfield investment dummy coefficient, and pre-cross-border dummy coefficient is equal to pre-greenfield investment dummy coefficient. Sectors are classified according to their mean share of intangible assets over non-financial fixed assets. High intangibles industries are the top quartile of all industries ranked by their respective mean share.

Table 3.9
Considering heterogeneity across modes of FDI and industries – Productivity estimation with OLS.

	Low intangibles	High intangibles
Estimated coefficients		
Future export expanding firm	0.214***	0.090**
	(0.013)	(0.038)
Future cross-border acquirer	0.115	0.526***
	(0.080)	(0.160)
Future greenfield investor	0.246***	0.046
	(0.027)	(0.051)
Test of equality of coefficients		
Future exporter = Future acquirer	0.099	-0.436***
	(0.081)	(0.162)
Future exporter = Future greenfield	-0.032	0.044
	(0.031)	(0.064)
Future acquirer = Future greenfield	-0.132	0.479***
	(0.171)	(0.277)
Past international activity	Yes	Yes
Control variables	Yes	Yes
Industry and time effects	Yes	Yes
N	212,767	36,247
adjusted R^2	0.400	0.503

Coefficients from an OLS regression with the residual from a OLS productivity estimation as the dependent variable (estimated standard errors in parentheses). ***, **, * denote significance levels 1, 5, 10%, respectively. Control variables: log number of employees, log number of employees squared, log average wage, log age, squared log age, foreign majority shareholder dummy, legal form dummy, log capital stock, exporter, post-cross-border deal and post-greenfield investment dummies, and a set of time and two-digit NACE industry dummies. Standard errors in parentheses. Two-sided t-test with null hypothesis pre-exporting dummy coefficient is equal to pre-cross-border dummy coefficient, pre-exporting dummy coefficient is equal to pre-greenfield investment dummy coefficient, and pre-cross-border dummy coefficient is equal to pre-greenfield investment dummy coefficient. Sectors are classified according to their mean share of intangible assets over non-financial fixed assets. High intangibles industries are the top quartile of all industries ranked by their respective mean share.

Table 3.10
Considering heterogeneity across modes of FDI and industries – Productivity estimation with fixed effects.

	Low intangibles	High intangibles
Estimated coefficients		
Future export expanding firm	0.342***	0.126***
	(0.014)	(0.038)
Future cross-border acquirer	0.405***	0.745***
	(0.088)	(0.153)
Future greenfield investor	0.590***	0.440***
	(0.029)	(0.059)
Test of equality of coefficients		
Future exporter = Future acquirer	-0.064	-0.619***
	(0.089)	(0.156)
Future exporter = Future greenfield	-0.249***	-0.315***
	(0.032)	(0.071)
Future acquirer = Future greenfield	-0.185**	0.304*
	(0.094)	(0.166)
Past international activity	Yes	Yes
Control variables	Yes	Yes
Industry and time effects	Yes	Yes
N	212,767	36,247
adjusted R^2	0.186	0.252

Coefficients from an OLS regression with the residual from a productivity estimation including fixed effects as the dependent variable (estimated standard errors in parentheses). ***, **, * denote significance levels 1, 5, 10%, respectively. Control variables: exporter, post-cross-border deal and post-greenfield investment dummies, and a set of time and two-digit NACE industry dummies. Standard errors in parentheses. Two-sided t-test with null hypothesis pre-exporting dummy coefficient is equal to pre-cross-border dummy coefficient, pre-exporting dummy coefficient is equal to pre-greenfield investment dummy coefficient, and pre-cross-border dummy coefficient is equal to pre-greenfield investment dummy coefficient. Sectors are classified according to their mean share of intangible assets over non-financial fixed assets. High intangibles industries are the top quartile of all industries ranked by their respective mean share.

Table 3.11
Considering heterogeneity across modes of FDI and industries – Alternative exporter definition.

	Low intangibles	High intangibles
Estimated coefficients		
Future exporting firm	0.086***	0.052
	(0.014)	(0.034)
Future cross-border acquirer	-0.004	0.424***
	(0.074)	(0.125)
Future greenfield investor	0.120***	-0.019
	(0.025)	(0.045)
Test of equality of coefficients		
Future exporter = Future acquirer	0.090	-0.372***
	(0.075)	(0.130)
Future exporter = Future greenfield	-0.033**	0.071*
	(0.028)	(0.058)
Future acquirer = Future greenfield	-0.124*	0.443
	(0.079)	(0.130)
Past international activity	Yes	Yes
Control variables	Yes	Yes
Industry and time effects	Yes	Yes
N	212,767	36,247
adjusted R^2	0.468	0.555

Coefficients from an OLS regression with Olley & Pakes log TFP as the dependent variable (estimated standard errors in parentheses). Exporter dummy equals one if firm starts to export within the next three years. ***, **, * denote significance levels 1, 5, 10%, respectively. Control variables: exporter, post-cross-border deal and post-greenfield investment dummies, and a set of time and two-digit NACE industry dummies. Standard errors in parentheses. Two-sided t-test with null hypothesis pre-exporting dummy coefficient is equal to pre-cross-border dummy coefficient, pre-exporting dummy coefficient is equal to pre-greenfield investment dummy coefficient, and pre-cross-border dummy coefficient is equal to pre-greenfield investment dummy coefficient. Sectors are classified according to their mean share of intangible assets over non-financial fixed assets. High intangibles industries are the top quartile of all industries ranked by their respective mean share.

Table 3.12
Considering heterogeneity across modes of FDI and industries – Interaction with industry share of intangible assets.

Estimated coefficients	
Future export expanding firm	0.105***
	(0.036)
Future cross-border acquirer	-0.354*
	(0.190)
Future greenfield investor	0.130**
	(0.063)
Future export expanding firm	-0.817
*mean R&D	(0.678)
Future cross-border acquirer	8.325**
*mean R&D	(3.470)
Future greenfield investor	-0.377
*mean R&D	(1.070)
Past international activity	Yes
Control variables	Yes
Industry and time effects	Yes
N	249,014
adjusted R^2	0.478

Coefficients from an OLS regression with Olley & Pakes log TFP as the dependent variable (estimated standard errors in parentheses). ***, **, * denote significance levels 1, 5, 10%, respectively. Control variables: log number of employees, log number of employees squared, log average wage, log age, squared log age, foreign majority shareholder dummy. Standard errors in parentheses. Two-sided t-test with null hypotheses pre-internationalization dummy coefficient and interaction term coefficient jointly equal to zero.

Table 3.13
Considering heterogeneity across modes of FDI and industries – Manufacturing and service industries.

	Services	Manufacturing
Estimated coefficients		
Future export expanding firm	0.075***	0.039***
	(0.016)	(0.014)
Future cross-border acquirer	0.009	0.176**
	(0.089)	(0.077)
Future greenfield investor	0.141***	0.035
	(0.030)	(0.028)
Test of equality of coefficients		
Future exporter = Future acquirer	0.066	-0.137*
	(0.091)	(0.078)
Future exporter = Future greenfield	-0.066*	0.004
	(0.034)	(0.032)
Future acquirer = Future greenfield	-0.133	0.141*
	(0.096)	(0.082)
Past international activity	Yes	Yes
Control variables	Yes	Yes
Industry and time effects	Yes	Yes
N	195,193	53,821
adjusted R^2	0.488	0.417

Coefficients from an OLS regression with Olley & Pakes log TFP as the dependent variable (estimated standard errors in parentheses). ***, **, * denote significance levels 1, 5, 10%, respectively. Control variables: log number of employees, log number of employees squared, log average wage, log age, squared log age, foreign majority shareholder dummy, legal form dummy, log capital stock, exporter, post-cross-border deal and post-greenfield investment dummies, and a set of time and two-digit NACE industry dummies. Standard errors in parentheses. Two-sided t-test with null hypothesis pre-exporting dummy coefficient is equal to pre-cross-border dummy coefficient, pre-exporting dummy coefficient is equal to pre-greenfield investment dummy coefficient, and pre-cross-border dummy coefficient is equal to pre-greenfield investment dummy coefficient. Manufacturing industries: two-digit NACE codes 15-37.

Table 3.14
Considering heterogeneity across modes of FDI and industries – R&D intensity (manufacturing only).

	Low R&D	High R&D
Estimated coefficients		
Future export expanding firm	0.059***	-0.006
	(0.016)	(0.027)
Future cross-border acquirer	0.006	0.318***
	(0.090)	(0.111)
Future greenfield investor	0.055*	-0.004
	(0.031)	(0.050)
Test of equality of coefficients		
Future exporter = Future acquirer	0.053	-0.324***
	(0.092)	(0.114)
Future exporter = Future Greenfield	0.003	-0.002
	(0.035)	(0.058)
Future acquirer = Future Greenfield	-0.049	0.321***
	(0.097)	(0.119)
Past international activity	Yes	Yes
Control variables	Yes	Yes
Industry and time effects	Yes	Yes
N	37,490	15,940
adjusted R^2	0.434	0.394

Coefficients from an OLS regression with Olley & Pakes log TFP as the dependent variable (estimated standard errors in parentheses). ***, **, * denote significance levels 1, 5, 10%, respectively. Control variables: log number of employees, log number of employees squared, log average wage, log age, squared log age, foreign majority shareholder dummy, legal form dummy, log capital stock, exporter, post-cross-border deal and post-greenfield investment dummies, and a set of time and two-digit NACE industry dummies. Standard errors in parentheses. Two-sided t-test with null hypothesis pre-exporting dummy coefficient is equal to pre-cross-border dummy coefficient, pre-exporting dummy coefficient is equal to pre-greenfield investment dummy coefficient, and pre-cross-border dummy coefficient is equal to pre-greenfield investment dummy coefficient. Manufacturing industries: two-digit NACE codes 15-37.

Table 3.15
Considering heterogeneity across modes of FDI and industries – Advertising intensity (manufacturing only).

	Low advertising	High advertising
Estimated coefficients		
Future export expanding firm	0.011	0.135***
	(0.016)	(0.031)
Future cross-border acquirer	0.039	0.452***
	(0.071)	(0.153)
Future greenfield investor	0.015	0.089*
	(0.033)	(0.050)
Test of equality of coefficients		
Future exporter = Future acquirer	-0.028	-0.317**
	(0.073)	(0.156)
Future exporter = Future Greenfield	-0.004	0.046
	(0.037)	(0.058)
Future acquirer = Future Greenfield	0.023	0.364**
	(0.081)	(0.158)
Past international activity	Yes	Yes
Control variables	Yes	Yes
Industry and time effects	Yes	Yes
N	38,311	15,119
adjusted R^2	0.402	0.470

Coefficients from an OLS regression with Olley & Pakes log TFP as the dependent variable (estimated standard errors in parentheses). ***, **, * denote significance levels 1, 5, 10%, respectively. Control variables: log number of employees, log number of employees squared, log average wage, log age, squared log age, foreign majority shareholder dummy, legal form dummy, log capital stock, exporter, post-cross-border deal and post-greenfield investment dummies, and a set of time and two-digit NACE industry dummies. Standard errors in parentheses. Two-sided t-test with null hypothesis pre-exporting dummy coefficient is equal to pre-cross-border dummy coefficient, pre-exporting dummy coefficient is equal to pre-greenfield investment dummy coefficient, and pre-cross-border dummy coefficient is equal to pre-greenfield investment dummy coefficient. Manufacturing industries: two-digit NACE codes 15-37.

Chapter 4

Who buys who in international trade

4.1 Introduction

Firm heterogeneity has dominated international trade theory and empirics more than any other topic in the last decade. Today, the selection of firms into different types of international activities according to their size, productivity, and other characteristics has become a stylized fact. Only the best firms within an industry become MNEs, while the second best firms find it more profitable to export their goods to the foreign market, and the less productive firms serve the domestic market only (Melitz, 2003; Helpman et al., 2004; Bernard et al., 2007b). In addition, several papers indicate that firms acquired by foreign owners are not a random sample either. In contrast, foreign-owned firms are often shown to outperform domestic firms of the same industry. At least part of this superior performance seems to arise because multinationals cherry-pick better than average firms as potential acquisition targets (Almeida, 2007; Arnold & Javorcik, 2009). These two aspects, however, are usually addressed separately in the literature. Using a European firm-level dataset in combination with a global M&A database, I am able to analyze the complete sorting of acquirers and targets and to compare the ranking for national and cross-border acquisitions. Further, I link directly acquirers to their respective target firms, which allows me to provide first evidence on the question of who buys who in international trade.

In the finance literature, that traditionally focuses on national mergers and acquisitions, the debate of who buys who has been discussed since the first larger wave of M&As in the 1980s, and the issue remained an active research question ever since. While Jovanovic & Rousseau (2002) describe in their q-theory of mergers how firms with high market-to-book ratios exploit their advantage to buy undervalued firms, Rhodes-Kropf & Robinson (2008) suggest that firms with rather similar market-to-book values tend to merge. In contrast to these studies, Maksimovic & Phillips (2001) focus on the productivity of the merging parties and confirm a reallocation of resources from inefficient to better firms. Yang (2008), finally, adds another dimension to the problem and shows that *changes* in productivity rather than productivity *levels* are important determinants of real asset sales and acquisitions. Firms experiencing positive productivity growth typically acquire firms, while firms with decreasing productivity sell off their assets.

No comparable study exists with a particular focus on international acquisitions. Most trade models that incorporate heterogeneous firms and MNEs assume that all FDI are greenfield investments (Helpman et al., 2004; Neary, 2007). No predictions are made regarding who buys who. One of the few theoretical papers that looks at cross-border acquisitions in an international trade model explicitly is Nocke & Yeaple (2007). They stress the access to complementary assets as the motivation for M&A across borders. Cross-border acquirers can be at the upper or lower range of the productivity distribution of internationally active firms depending on industry characteristics. The predictions regarding who buys who is not addressed explicitly, however, as the better of the two merging firms is exogenously defined to be the acquirer in the deal. In the model of Neary (2007), strategic considerations of the firms result in merger waves, in which high efficiency firms buy less efficient foreign firms contributing to the specialization of countries in activities in which they have a comparative advantage. However, firms within industries are not heterogeneous. Breinlich (2008) examines the impact of trade liberalization on national and cross-border M&A activities in North America. He finds that on average, acquirers are more productive than targets, except for acquisitions of U.S. targets by Canadian firms. However, he looks at the differences ex-post and does not link the two sides of the deals directly.

The present paper extends and contributes to both strands of literature. Enriching a European M&A database with firm characteristics of both the acquiring firms and the corresponding acquisition targets, I am able to analyze both sides of European cross-border acquisitions simultaneously in one linked dataset. I further add a large random sample of firms that are not involved in any M&A deal over the period of observation as a control group to account for country and industry differences.

The novel features of the analyses are, first, that I am able provide the complete ranking of acquirer and target firms compared to a large sample of non-participating control firms for a series of performance measures. Second, as my sample is not restricted to one country only, the results regarding the selection of acquirers and picking of targets are more reliable than in studies based on a single country. Third, I focus on the explicit match of acquirer and target firms according to their pre-acquisition characteristics, which provides a direct comparison between the participating parties. The analysis thus extends the question of who buys who to international acquisitions. Finally, differences between national and cross-border deals are considered.

Heterogeneity in the pre-acquisition performance differences between acquirer and target firms can help to explain why the empirical work on spillover effects of foreign firms on domestic target firms has not provided consistent results so far. Maksimovic & Phillips (2001) note that productivity improvements depend on the superior technology of the acquiring firm. As the effect of foreign ownership probably depends on the actual productivity edge of the acquiring firm, the analysis of the actual combinations of targets and acquirers can help to explain the observed heterogeneous effects of foreign acquisitions.

In line with previous work, I find robust evidence both for the selection of the best acquirers and the cherry picking of above-average target firms according to several performance measures. Cross-border acquirers are on average larger and more productive than target firms and those are again better than domestic firms not involved in any acquisition. The ranking of acquirer and target firms holds also for national deals, but on a lower level. Additionally, acquirers are firms that grow in size, while in national deals, firms with an on average positive productivity change are taken over.

With the direct link of firms involved in a deal, I find that the performance differences between acquirers and targets are quite heterogeneous. On average, larger and more productive firms acquire smaller firms. The performance difference is smaller for domestic deals. The distribution of acquirer-target difference is more concentrated around zero for domestic deals, while size differences in cross-border M&As appear to be more heterogeneous and are also more often positive than in national acquisitions. The results suggest that "high buys less high" might be the best characterization of firm matches in cross-border acquisitions, while "like buys like" is more typical for national deals. Although it seems to be more frequent in international M&A deals that efficient firms pick less efficient still but above-average performing targets, there is a large heterogeneity in the matches of acquirers and target firms.

The paper proceeds as follows. The next section summarizes the existing literature. In section 4.3, the construction of the dataset is described, the variable definitions can be found in section 4.4 and section 4.6 discusses the results. The last section concludes the paper.

4.2 Related literature

The question of who buys who has a long tradition in the finance literature. The view that acquirers are better than their targets goes back to the work of Manne

(1965). He sees mergers as an alternative to bankruptcy and liquidation through which badly managed, low valued resources are reallocated to more efficient managements. Similarly, Jovanovic & Rousseau (2002) use the well-established q-theory of investments to explain why mergers occur. They see mergers as a type of investment that provides an alternative to purchasing disassembled capital. Firms with high market-to-book ratios should invest in firms with less growth opportunities, reflected in lower valuations, as they are able to transfer their higher efficiency to the acquired assets. The idea of mergers as reallocation of assets to more efficient uses results in the prediction that "high buys low". Andrade et al. (2001) support these findings stating that more than 60% of all deals involve acquirers with higher market-to-book ratios compared to the respective targets, and the median relative size is between 10 to 13%.

Rhodes-Kropf et al. (2005), on the other hand, question this view by their empirical evidence of U.S. domestic mergers. They indeed find that acquirers' valuations are on average higher than target firms' valuations. However, targets are also valued significantly higher compared to domestic firms. They suggest that "high buys less high" instead of "high buys low" might be a better description of the firms' sorting pattern. Rhodes-Kropf & Robinson (2008) formulate even stronger results: they show that on average, targets and acquirers are quite similar to each other and propose "high buys high, moderate buys moderate, and low buys low" (p.1170) or "like buys like" to best describe the observed sorting mechanism. They offer a new theory of mergers that assumes that complementary assets should be bound together within a firm to reduce hold-up problems and underinvestment in the spirit of the well-known property rights approach. To realize the gains from complementary assets, firms have to negotiate with potential merger partners. Firms have to trade off higher gains from a better match with the reduced bargaining power in a merger process with a better partner. In the end, similar firms in terms of various dimensions will decide to combine their assets in a merger. The authors test the predictions of this model again using market-to-book-ratios. While the average valuation is higher for acquirers than for targets, examining the complete distribution reveals that the most frequent transaction type involves firms in the same range of the distribution of market-to-book ratios.

The model allows to make an interesting prediction for cross-border as opposed to national acquisitions. The acquirer-target differences in market-to-book ratios are expected to be smaller, the lower the search costs for a matching firm. Searching for suitable targets should be much more costly at a international scale than looking for the best match in the domestic market only. The "like buys like" effect should therefore be less pronounced in cross-border acquisitions compared to domestic deals.

A major drawback of the analyses of market-to-book ratios is the restriction to publicly listed firms. Only for those firms, the valuations can be derived from stock market data. Furthermore, as Maksimovic & Phillips (2001) point out, looking at productivity directly has the additional advantage compared to analyses of stock market data that market responses to the transaction and expectations of future effects on the merger parties' performance are not reflected in the measure but only actual productivity changes are considered (compare footnotes 6 and 8).

There are not many theoretical papers that explicitly take into account cross-border M&A, and to the best of my knowledge, there is no model that predicts the match between heterogeneous acquirers and their foreign acquisition targets endogenously.[1] One of the few theoretical papers that looks explicitly at cross-border acquisitions in an international trade model is Neary (2007). In his model, strategic considerations build the motivation for cross-border acquisitions for firms that compete in oligopolistic markets. He shows how merger waves emerge, in which high efficiency firms buy less efficient foreign firms contributing to the specialization of countries in activities in which they have a comparative advantage. While the model predicts a productivity advantage for foreign acquirers even in the absence of efficiency gains as a specific motive for the deal, his model does not feature within industry heterogeneity of firms. If one firm is taken over in an industry, all firms will be acquisition targets in the following merger wave.

Access to complementary technology is the main motivation for firms to enter the foreign market in the model of foreign market entry by Nocke & Yeaple (2007). In their model, firms of an industry are heterogeneous in their observed productivity due to differences in capabilities that are more or less mobile across borders, such as technological know-how or marketing skills, respectively. Domestic and cross-border mergers provide opportunities for firms to get access to location-specific assets that they can combine with their own capabilities. The predictions of the model regarding the efficiency of target firms differs depending on the type of industry considered. While targets in domestic and cross-border ac-

[1] There is a significant literature that looks at the effects of tariffs and trade liberalizations and merger policy on the choice of FDI mode. These models usually do not account for within industry firm heterogeneity.

quisitions should not differ in industries where internationally mobile capabilities matter most, foreign acquirers are predicted to be more efficient on average than domestic acquirers. In industries where within-industry productivity differences can be traced back to differences in non-mobile capabilities, in contrast, domestic targets are endowed with better capabilities compared to their cross-border counterparts, but the ranking of acquirers remains the same. Regarding the direct link between acquirers and targets, the model provides no testable predictions. Exogenously, the more productive firm is defined to be the acquirer.

Empirical evidence that is most related to this paper is provided by Breinlich (2008), who looks at domestic and cross-border acquisitions between Canadian and U.S. firms after trade liberalizations. He finds that on average acquirers are larger than target firms, whereas productivity differences appear to be less pronounced. He argues that this is generally in favor of the reallocation to efficient uses hypothesis. He also acknowledges that additional motives such as access to superior technology might overlap this regularity in some cases, as U.S. targets of Canadian acquirers tend to be smaller, but more productive. However, he looks at the differences ex-post and does not link the two sides of the deals directly. Further, the sample for this part of the analysis is also restricted to publicly traded firms.

The selection of firms into different types of international activities according to their size, productivity, and other characteristics is now well documented. Following the "new, new trade theory" (Melitz, 2003; Helpman et al., 2004), only the best firms within an industry become MNEs, while the second to best firms find it more profitable to export their goods to the foreign market, and the less productive firms serve the domestic market only.[2]

More recent work focuses on different types of foreign direct investment, namely cross-border M&As and greenfield entry. Nocke & Yeaple (2008) and Raff et al. (2012) compare both types of foreign market entry and find on average more productive firms to choose greenfield entry over acquisitions, while Trax (2011) shows for a British sample that the productivity ranking varies across industry types. Acquirers are the most productive firms in industries with a high ratio of intangible assets, but in other industries they are the least productive of all internationally active firms.

[2]see overview and survey by Bernard & Jensen (2007); Greenaway & Kneller (2007), for example, and Girma et al. (2005); Jäckle & Wamser (2010); Damijan et al. (2007) for more recent evidence on the productivity advantage of future multinational firms

In addition, several papers indicate that firms acquired by foreign owners are not a random sample either. In contrast, foreign-owned firms tend to outperform domestic firms of the same industry. Arnold & Javorcik (2009) named Indonesian targets of foreign owners "gifted kids", as at least part of their performance premium seems to arise because multinationals cherry-pick better than average firms as potential acquisition targets. Several other studies document cherry picking of productive firms by foreign new owners.[3]

Gioia & Thomsen (2004), in contrast, describe a lemon-picking behavior of foreign acquirers compared to domestic owners in Denmark. Conyon et al. (2002b) finds that in acquisitions of U.K. targets, both domestic and foreign acquirers choose plants with below-average size, but the effect is smaller for international acquisitions. They also provide descriptive evidence that both types of acquirers choose firms with positive employment and labor productivity growth, and this selection on productivity growth is stronger for targets of international investors.

There are not many papers that compare international with domestic acquisitions explicitly. Hanley & Zervos (2007) and Bertrand & Zitouna (2008) show that in contrast to domestic acquirers, foreign owners select their targets based on above average performance. For Norwegian manufacturing firms, Balsvik & Haller (2010) analyze pre-acquisition employment, wage, and productivity levels. They find that foreign new owners acquire large, productive, and also high-wage plants, while domestic acquirers also select bigger targets, but with only average productivity.

4.3 Data

The dataset for this study on both sides of cross-border investments is an innovative combination of a global M&A database with a European firm-level dataset. Next to various deal characteristics, the M&A database provides information on the firms involved in each deal. With this link between the two sides of a deal, the balance sheet data is merged twice to the list of M&A deals, first for the acquirer and second for the corresponding target firms. This combined dataset is then complemented

[3] McGuckin & Nguyen (1995) for targeted U.S. firms, Harris & Robinson (2002), Girma & Görg (2007) and Criscuolo & Martin (2009) for British firms, Almeida (2007) looks at Portuguese firms, and Karpaty (2007) for Swedish targets.

with an extensive random sample of control firms that are not involved in any acquisition in the period of observation. Table 4.1 shows the stylized structure of the resulting final dataset.

The transaction data is extracted from the Zephyr database that is published by Bureau van Dijk. The data are collected from company reports, regional information providers, consulting firms, and press releases. Zephyr includes data on a wide range of transactions, including M&A deals. It provides information about the date and value of a deal, the source of financing as well as a description of the type of transaction. Most importantly, it lists all firms that are involved in a deal.

In the sample, I include only completed deals in which the acquirer gains a majority interest. Furthermore, I exclude deals for which more than one acquirer is named. In cases where a acquirer consortium is listed that consists of one non-financial acquirer and financial firms, I do include the deal and refer to the characteristics of the non-financial acquirer. If the only acquirer belongs to the financial sector, the deal is dropped from the sample. There are some deals reported, in which more than one target is acquired at the same time, I treat those deals as separate deals for each target. Finally, I exclude acquisitions if firms change their majority owner more than once within one year, as determinants and effects of the single acquisitions could be confounded.

The firm data is taken from the Amadeus database that stems from the same data provider. Amadeus is a European firm-level dataset and it provides information on firms' balance sheets, and profit and loss accounts for up to ten years.[4] The data is collected from company reports that are supplemented by specialized regional information providers. For a cross-country study that links firms located in different countries, Amadeus has the important advantage that the process of data collection is as homogeneous as possible across countries.

A fundamental feature of the data is the availability of unconsolidated accounts that display balance sheet items separately for the single firm. As this is a necessary pre-condition for comparing acquirer and target characteristics, only firms for which unconsolidated balance sheet data are available are included in the sample. Firms that are active in the primary sector, holding companies (NACE code 7415), and firms from the public sector (NACE 75, 91) are deleted. I also exclude financial companies (NACE 65-67) as the definition of output or sales and is not comparable

[4]Eight yearly updates are merged for this analysis for the years 2000-2007.

to other firms. I further delete observations with implausible values such as negative input factors and with growth rates larger than the highest and smaller than the first 200-quantile, as those large changes might indicate unreported merger activity or other forms of organizational restructuring.

The Amadeus firm-level data has been analyzed in the empirical FDI literature quite frequently (see Egger et al., 2010; Helpman et al., 2004, as examples), the link to the merger information of Zephyr has been used by Stiebale & Trax (2011) and Trax (2011). The major advantage is the broad coverage of the dataset. A particularly interesting feature is the inclusion of non-listed firms, a restriction of several other datasets focusing on merger and acquisitions.

As typical for most firm-level datasets, the sample is somewhat biased towards the larger firms of the respective economies. While the smallest firms are typically not involved in acquisitions, deals where either the target or acquirer is relatively small might thus be not included. Nonetheless, it has been found that the sectoral and aggregate distribution of firm size and employment growth rates follow those from national labor force surveys and the OECD Stan database quite closely (see Messina & Vallanti, 2007, for instance).

A more serious problem arises with the link between target and acquirer information. One limitation of the Amadeus database is that values for key variables like sales, employment, or financial indicators are missing for some companies. Deals can only be included in the sample if all information for both acquirers and targets is available at the same time. The missing value problem is thus multiplied, which reduces the final sample size considerably. I therefore restrict the analysis to variables for which the missing value problem is less severe.[5]

Using the comprehensive information of the M&A database, I first identify which firms belong to the group of cross-border acquirers, cross-border targets, domestic acquirers, and domestic targets. Excluding all firms that appear at some point in time in the Zephyr database from the firm dataset, I draw a large random sample of domestic firms form a suitable control group. The number of control firms is proportional to the number of M&A participants in each country, industry, and year cell. The procedure ensures that for each deal enough observations are available while the size of the dataset remains manageable at the same time.

[5]For the same reason I cannot estimate the effects of acquisitions on the participating firms, as the sample shrinks even more when several years of observations are needed. In addition, for many targets no information is available after the acquisition.

4.4 Variables

In the analysis, I do not rely on one measure of productivity, but rather on a set of variables that measure firm size and technology. All variables are interesting in their own, but together, they create a broader picture of the factors driving the firms' internationalization decision.

The list of variables includes sales, employment, and capital to measure the firms' size in different dimensions. Capital is measured as non-financial fixed assets, employment is the headcount of employees, and the sales figure is the firms' reported turnover. The technology of the different groups of firms is characterized with their observed labor productivity, capital intensity, and total factor productivity (TFP). The TFP measure is calculated as the residual of a Cobb-Douglas production function, with the coefficients estimated with OLS. In addition to the standard inputs capital and labor, I control for the age and legal form of the firm, and I include dummy variables for industry, country, and year effects in the production function estimation.[6] All variables are used in logarithmic form. Next to the analysis of the performance measures in levels, I also consider performance changes. The log growth rate of each variable is constructed taking the difference between the logarithm in the year of interest minus the logarithm of the value that the respective variable takes on in the previous year.[7]

As further control variables, I generate the age of the firm as the number of years since incorporation that can be interpreted as a reflection of learning (Jovanovic, 1982) and is included as a control for growth potentials and experience. In addition, a dummy controlling for the legal form equals one if the acquirer is a public limited company. Differences in technological opportunities and the competitive environment are accounted for by industry dummies at the NACE two-digit industry level. Country specificities are captured by country fixed effects. A set of time dummies captures macroeconomic factors such as changes in the business cycle or exchange rate movements.

[6] I use this simple TFP measure, as the use of the procedures of Olley & Pakes (1996); Levinsohn & Petrin (2003) is impeded by differences in the availability of certain variables across countries. The same is true for value added as an alternative outcome variable.

[7] Log growth rates have the advantage that they are symmetric. Growth rates of the form $(x_t - x_{t-1})/x_{t-1}$ results in different values for an absolute increase and decrease of the variable of identical size, which is problematic in the calculation of averages.

The sample consists of firms from different countries and industries, and includes several years. Any absolute differences between firms would be hard to interpret in a meaningful way due to country, industry, and year effects. Moreover, the heterogeneous firms models usually refer to within industry variations in the firms' performance. To account for country, industry, and year specific effects, I include the appropriate sets of dummy variables in the estimations. For descriptive analyses and the Kolmogorov-Smirnov test, I construct z-scores for all variables, a dimensionless measure that is better comparable across firms.[8]

$$z(x_{it}) = \frac{x_{it} - m(x^c_{jkt})}{sd(x^c_{jkt})}, \tag{4.1}$$

with $z(x_{it})$ the calculated z-score of variable x_{it} for firm i in industry j, in country k, and year t. A z-score is a transformation that centers the distribution of a variable around zero and normalizes it with the variable's standard deviation. That is, I calculate for all variables the respective means $m(x^c_{jkt})$ and standard deviations $sd(x^c_{jkt})$ for all country, industry, and year cells. The calculations are based exclusively on the observations of the control sample. The interpretation of the generated z-scores is thus the following. What is the distance of the respective observation to the sample mean of the control firms in the firms' country, industry, and year cell in numbers of standard deviations. It gives us the position of the observation in the within country-industry distribution of non-merging firms in a given year. This normalization makes the variables comparable across countries.

The panel structure of the data allows to focus on pre-acquisition characteristics in the years before the actual merger takes place. This is important to make sure that the selection of firms is captured, but not the reverse effects of M&As on characteristics of the participating firms (Bernard & Jensen, 1999). As the accounting-based variables used in the analysis might be affected by the firms' merger activity, using contemporaneous values of the performance measures is inappropriate as it would introduce spurious correlation (Andrade & Stafford, 2004). All explanatory variables are thus always as of the beginning of the period, i.e. lagged by one year.

[8] As the population means and standard deviations are not known, the sample analogues from the random control sample are used. This transformation more exactly should be called a t-statistic. However, with large sample sizes, the t-statistic is asymptotically normally distributed and the term z-scores is normally used in the literature.

4.5 Estimation

In the literature that tests performance premia of different firm groups, two approaches co-exist. The productivity advantages are easily estimated in a regression of the respective performance measure on a set of dummies for each type of firm as in Bernard & Jensen (1999) and Head & Ries (2003). The alternative strategy is to test for differences in the productivity distributions between groups of firms using Kolmogorov-Smirnov test similar to Delgado et al. (2002) and Girma et al. (2005). The first variant gives better insights in the size of the premium. The latter approach has the advantage that the non-parametric test is not restricted to the sample mean, but takes the complete distribution of the tested variables into account. As both methods have their own advantages, I decide to perform both approaches.

First, I estimate the following equation for each performance measure x:

$$\begin{aligned} ln(\mathrm{x}_{it}) &= \alpha_0 + \alpha_1 CBAC_{it} + \alpha_2 CBTA_{it} + \alpha_3 NAAC_{it} + \alpha_4 NATA_{it} \\ &+ \gamma_j + \gamma_k + \gamma_t + \varepsilon_{it}, \end{aligned} \tag{4.2}$$

where $CBAC_{it}$ refers to cross-border acquirers, $CBTA_{it}$ to targets in a cross-border deal, $NAAC_{it}$ to firms engaged as acquirers in national deals, and $NATA_{it}$ are the respective national targets. The reference category is formed by the control firms that are not involved in any merger activity in the observation period. Dummy variable sets for countries, industries, and years are included so that the comparisons across firm groups refer to within industry differences. As stressed earlier, the equation refers strictly to the period before the actual merger takes place to single out the selection of firms.

The estimated coefficients α_k of the firm type dummies reflect the performance premium of the corresponding group of firms in comparison to the control group that is not involved in any merger activity. To test whether firms of group k are significantly more or less productive than firms in group l, two-sided t-tests of the following null hypothesis are performed:

$$H_0 : \alpha_l - \alpha_k = 0, \tag{4.3}$$

where α_k and α_l are the estimated coefficients and $k, l \in 1, 2, 3, 4$. If the null hypothesis of no differences can be rejected, the performance premia for the respective firm types differ significantly from each other.

The second approach compares the complete distribution of the performance measures across firm groups. The non-parametric Kolmogorov-Smirnov test relies on the concept of first-order stochastic dominance and establishes a ranking for the compared distributions. Given the empirical cumulative distribution functions of the performance measure x of two groups of firms, $F(x)$ and $G(x)$, stochastic dominance of $F(x)$ over $G(x)$ implies that $F(x) - G(x) \leq 0$ over x, and $F(x) - G(x) < 0$ for at least some x.

Following Delgado et al. (2002) and others, two tests are needed to establish stochastic dominance of one distribution over another. The two-sided Kolmogorov-Smirnov test on equality of distributions has the following null-hypothesis:

$$H_0 : F(x) - G(x) = 0 \quad \text{for all } x \quad ; \quad H_1 : F(x) - G(x) \neq 0 \quad \text{for some } x. \tag{4.4}$$

If the two distributions are not identical, the null of this test is rejected. If this is the case, we look at the one-sided Kolmogorov-Smirnov test to determine whether one distribution dominates the other.

$$H_0 : F(x) - G(x) \leq 0 \quad \text{for all } x \quad ; \quad H_1 : F(x) - G(x) > 0 \quad \text{for some } x. \tag{4.5}$$

If this test cannot be rejected, the distribution $F(x)$ dominates, and therefore lies to the right of $G(x)$.

The Kolmogorov-Smirnov test compares the cumulative distribution functions of the various variables calculated for each firm group separately. Plotted in a graph, a distribution stochastically dominates the other one if it is located to the right of that distribution. The Kolmogorov-Smirnov test calculates the maximum vertical distance between two different distribution functions (D). If one distribution stochastically dominates the other significantly, this measure should be large enough so that the distance between the two distributions cannot be explained by random sampling error. However, with this simple test statistic, the Kolmogorov-Smirnov test does not work properly, when the two distributions intersect. Hence, a visual inspection of the graphs complements the analysis.

The test is applied to the standardized values of the variables (z-scores) to filter out country, industry, and time specific effects that might vary between groups.

4.6 Results

4.6.1 Deal characteristics

In this section, I start with a general overview of the M&A deals in the sample. Table 4.3 provides a list of observations per firm group and country, tables 4.5 and 4.6 tabulate the industry distribution of acquirers, targets, and control firms, and table 4.2 shows the distribution of deals over the period of observation.

Overall, the sample contains information on both sides of the deal for 482 cross-border deals and 2,288 national acquisitions. 58,843 firms are chosen as control firms. Table 4.2 displays the number of cross-border and national deals over time for the years 2001–2007.[9] The period of observation covers the end of the merger wave that had its peak in 2001 and includes the start of the latest merger wave in 2006/2007 that was ended by the start of the financial crisis.

France and Germany are known to be among the top countries with respect to the number of acquisitions. The numbers for the United Kingdom are unfortunately too low (compare Brakman et al., 2007a). While in principle many British deals are recorded for this country in Amadeus and Zephyr, the link between both sides of the deal turns out to perform very poorly for this country. The main reason is that British firms invest overseas much more frequently than acquirers in continental Europe. As only information on mergers within Europe is in the sample, those deals are excluded. On average, there are four to five times more national deals per country in the sample than cross-border acquisitions with the exception of Spain, where the domestic merger market has been much more active, probably due to deregulations in several industries. Table 4.4 lists the top ten of the country pairs observed in the sample. The numbers illustrate nicely that most of the cross-border acquisitions are observed in both directions between rather similar and close country pairs. Figure 4.1, finally, shows the distribution of cross-border deals that take place between different Western European countries, between Eastern European countries, and investments with participating firms from both broad regions. Most deals involve only firms from western countries, some investments from western countries in the Eastern European region can be observed, but the number of deals in the other direction and between Eastern European firms is negligible. Cross-border M&A is a business between firms of the largest, most developed countries.

[9] I restrict the analysis of the distribution of deals to the number of deals, as the alternative measure in terms of deal values is not disclosed in many cases.

The merger activity is not restricted to the manufacturing sector. The chemical industry and manufacturing of food products are characterized by a high merger activity, as well as there a many deals in the construction sector. But most frequently, both national and domestic M&A occur in the computer business and in other business related activities in the sample.

Theoretical models discriminate between horizontal and vertical investments. The motivation for horizontal FDI is the duplication of the production process to serve a foreign market in the spirit of Markusen (1984) and Brainard (1997). Vertical investments shift parts of the production process abroad to take advantage of cross-country cost differences (Helpman, 1984; Alfaro & Charlton, 2009). While this differentiation is difficult to measure directly in empirical work, a frequently used approximation of these two types of FDI are within- and cross-industry investments. Deals between firms that operate in the same two-digit NACE industry are labeled as related deals and should capture horizontal investment motives. Acquisitions of firms in different sectors are referred to as unrelated deals.

The share of related cross-border deals is on average 54.8%, and thus comparable to the figures in Brakman et al. (2007b). Almost the same share of national deals are investments in firms of the same industry (58.6%, compare figure 4.2). Between the “old” European countries in the West and the Eastern European countries, there is still a pronounced differnce in production and in particular in labor costs that could provide incentives for vertical investments. The share of both types of deals is basically the same for deals between firms in Western Europe and deals where Western European firms invest in the Eastern European countries (figure 4.3).

4.6.2 Performance ranking

The simple means of the different performance measures in levels are shown in the upper panel of table 4.7, the lower part summarizes the corresponding z-scores. Cross-border acquirers display the largest means of all variables in levels. The next higher figures show up for national acquirers. Cross-border targets, in turn, have slightly lower performance on average, but still larger than firms that are targeted in national deals. The ranking is the same for the transformed values. However, the absolute values of the means of the z-scores are smaller and the group means are closer to each other as country, industry, and year effects are eliminated. The values for the control firms are by definition close to zero with a standard error close to one. Cross-border acquirers’ log sales, capital, and labor are on average around two and a half standard deviations away from the average control firm. The distance is smaller for the other three measures, labor productivity, capital intensity, and the TFP measure. Hence, firms engaged in either side of a national or cross-border acquisition are much larger than control firms in the same industry. They are also more productive, but their advantage is smaller in numbers of standard deviations.

Regarding the growth variables (table 4.8), unconditional on any firm characteristics, the two groups of acquirers exhibit the strongest growth in size, where national acquirers experience even higher rates compared to cross-border acquirers. Interestingly, both groups of target firms show a reduction in their capital stock and capital intensity in the pre-acquisition period. Surprisingly, target firms are the only firms whose productivity levels increase. The z-scores of the growth variables reveal that corrected for the country, industry, and year composition, both types of acquirers grow more in size and productivity than the control sample and are rather similar to each other. For cross-border targets, most values are close to zero or negative. However, for both target groups, the mean TFP growth is positive, in the case of national target firms even higher than for their acquirers. National targets additionally experience a higher labor growth compared to non-merging firms.

To test the significance of the differences in means between groups, equation 4.2 is estimated. In addition to the three dummy variable sets for the firms' country, industry, and year, I include the age of the firm and a legal form dummy as further control variables in the regressions. Table 4.9 lists the estimated coefficients in the upper panel, the lower panel displays the test statistics and p-values for the t-tests on equality of coefficients. A significant estimated coefficient in the upper panel reveals a performance premium of the respective group compared to control firms. A significant positive value of a test statistic in the lower panel, indicates a superior performance of the group mentioned first in the respective row.

All types of firms display a significant higher performance level in each dimension compared to the reference group of non-merging firms. The size of the coefficients reflect the ranking found in the simple means. The differences between groups have all the expected direction and are significant in almost all cases. The only two exceptions are national acquirers and cross-border targets that are similar in terms of productivity. Cross-border and national targets further have about the same TFP levels. Thus, larger and more productive firms select themselves into both types of deals, with an additional premium for cross-border acquirers. But target firms are also a positive selection from the remaining pool of firms. According to the results so far, “high buys less high” would characterize the deals in sample.

The results are less clear, when changes in the performance of firms are considered (table 4.10). The size measures of acquirers grow faster both compared to control firms and also relative to the target firms. Targets experience a decrease in capital intensity, but their productivity growth is significantly higher than for non-merging firms. The two groups of targets exhibit similar changes in all variables, and the growth rates of the two groups of acquirers are also not significantly different from each other. Interestingly, in national deals, targets display a higher rate of productivity growth than the corresponding group of national acquirers.

As the sorting pattern of acquirers and targets might depend on the underlying characteristics of the M&A, I tried several sample splits. The results are largely the same for manufacturing and service firms, and also for firms in the high-tech and knowledge-intensive sector as opposed to low-tech and and less knowledge-intensive industries. A split of the sample in the period before and after 2004, the year when the new member states in the east of Europe joined the European Union and the starting point for the recent increase in merger activities, also did not provide any more insights. The productivity ranking across acquirers and targets thus seems to be quite robust across industries.[10]

The results are also basically the same for related deals (table 4.11), while cross-border and national targets do not differ in none of the performance measures in unrelated acquisitions (table 4.12). The superior productivity growth of national targets compared to national acquirers is found only in related deals. Targets in unrelated deals further do not display a lower investment rate than control firms, the lower capital growth is also driven by horizontal deals only (tables 4.13 and 4.14).

The Kolmogorov-Smirnov tests of stochastic dominance extend the comparisons from the first moments of the performance measures to the comparison of the complete distribution between firm groups. Table 4.15 and 4.16 show the results for the variables in levels. In table 4.17 and 4.17, differences in the growth rates are tested. For each variable and firm group pair, two test statistics (D) and the corresponding p-values are presented. The first lines shows the results for the

[10]Results for these variations are therefore not shown, but are available upon request.

two-sided test on equality of distributions. If the null of identical distributions is rejected, we look at the second, one-sided test on the stochastic dominance of one distribution. If the null of stochastic dominance cannot be rejected, the ranking of the two distributions is as indicated in the header of the respective column.

The Kolmogorov-Smirnov test results confirm the ranking of distributions for almost all variables and firm groups. For the performance measures in levels, the only exceptions concern the comparison of targets, where the Kolmogorov-Smirnov test indicates superior TFP for firms with a future foreign ownership change. For the differences in the groups' growth rates, the main results are identical to the evidence found with the mean comparisons as well. The sales growth distribution of cross-border targets dominates the distribution of national targets, and national targets in turn outperform domestic firms, though the coefficients in the t-tests were not significant. Finally, the difference between cross-border and national acquirers' TFP growth turns now out to be significantly positive.

As the ranking is rather similar for the three size and three productivity measures in levels, I draw the cumulative distribution functions for sales and labor productivity only in figure 4.4. The upper left plot shows the clear ranking of the sales distributions: cross-border acquirers, national acquirers, cross-border targets, national targets, and domestic firms. The differences between the two types of acquirers and the two groups of target firms become smaller, when the z-scores are considered in the upper right plot. At the same time, the distance between acquirers and targets becomes more pronounced. The lower two graphs show the same for labor productivity. Though the distributions are very close to each other, the same ranking can be observed.

All in all, the results so far are in line with previous work. Cross-border acquirers are on average larger and more productive than target firms and those are again better than domestic firms not involved in an acquisition even after correcting for industry composition and year effects. The ranking of acquirers and target firms also holds for national deals, but on a lower level. Some differences are observed for related and cross-industry deals, overall, however, the ranking is rather robust. Hence, both the selection of the best firms into acquisitions and the cherry-picking of above-average targets are present in the European M&A deals of the sample.

With regard to differences in the acquirers' and targets' growth rates, the ranking is less clear. Acquirers display the highest growth in the size measures. Targets in both deals have on average lower net investments, which is also reflected in a relative decrease in capital intensity. In contrast, target firms seem to experience an increase in their TFP measure one year before they are acquired, while acquirers do not experience an above-average productivity growth.

4.6.3 Who buys who

In this subsection, I use the direct link between acquirer and target firms to analyze acquirer-target performance differences to describe who buys who in domestic and international acquisitions.

The upper panel of table 4.19 depicts several descriptive statistics of the absolute difference between acquirers and targets with respect to the different performance measures. The lower panel shows the same values using the difference in z-scores. A positive value for the untransformed difference indicates that the acquirer has an absolute performance advantage in direct comparison to its target firm. A positive differences in z-scores indicates that the relative performance position of the acquirer within its industry is larger than the relative performance of its target in numbers of standard deviations.

The first columns of table 4.19 reveal that the absolute difference between acquirers and targets is positive on average for both types of deals and across all performance measures. The performance edge is somewhat larger in cross-border acquisitions. On average, the acquirer is one standard deviation further to the right in the standardized size distribution compared to the firm's future target. The differences are smaller, but still positive, for the productivity measures. The medians of the distributions of acquirer-target differences are also positive, and their values are larger for cross-border acquisitions. More than half of the deals involve a larger and more productive acquiring firm relative to its target.

Looking at the the 25^{th} and 75^{th} percentiles depicted in the remaining columns helps to get a better feeling for the shape of the complete distributions. For the absolute differences in the size variables, both the 25^{th} and 75^{th} percentiles are positive, and larger for cross-border acquisitions compared to national deals. That means that in at least three quarter of all deals, a larger acquirer and a smaller target are involved. In fact, the previous result of "high buys less high" seems to be confirmed. Acquirers are better than their targets, but as we have seen in the previous section, targets are still above-average firms compared to the control group of non-merging firms. All percentiles display a higher figure for cross-border deals. That means that the performance premium is on average even higher for international acquisitions.

The distributions of the different productivity measures are closer to zero, as the 25^{th} percentiles are negative. There are more cases, in which a less productive acquirer is involved, the majority of the deals, however, indeed implies a transfer of resources to more efficient firms in absolute terms.

After the standardization, the means and medians of the distribution of size differences in z-scores are still larger in international deals, but the figures are now very close to the values for national deals. However, the spread of the distribution is larger for almost all performance measures, as the 25^{th} percentile is lower, but the 75^{th} percentile is higher compared to the values of national deals. Also, the standard deviation of the differences in z-scores are higher in the cross-border sample.

Table 4.20 shows the descriptive statistics for the distance between acquirer and target firms with respect to their performance growth. All in all, acquirers and targets are similar in their absolute growth rates. Considering the differences in z-scores, however, cross-border acquirers appear to have on average higher relative growth rates than their targets. The only exception is TFP growth, where the median difference in z-scores is close to zero, but the average TFP growth difference is negative. Only half of the deals are between acquirers with superior TFP growth, while targets often display higher growth rates than their acquirers.

The distributions of absolute differences in growth rates for national deals is rather similar to the findings for cross-border deals. However, even after standardization, the growth rates of national acquirers and targets are very close to each other. The only exceptions are that national acquirers seem to increase their capital stock more than their future target firms. Similar to cross-border acquisitions, the mean productivity difference in z-scores is also negative for national acquisitions.

To test whether the acquirer-target performance differences are significantly larger for cross-border deals, I regress the calculated differences for each performance measure on a dummy variable that takes the value one if the deal is an international transaction. These regressions now contain two country and two industry dummy variable sets, one for acquirer and one for target firms, respectively. The estimated coefficients are displayed in table 4.21. In the first row, we see that for all measures, the performance differences in cross-border acquisitions are indeed larger compared to national deals. The larger differences mainly stem from related deals (second row), while in acquisitions across industries, only the sales and labor productivity spread is larger for cross-border acquirers (third row). As indicated in the descriptive statistics, the lower panel reveals no significantly larger acquirer-target growth difference for international acquisitions.[11]

Figure 4.5 is illustrative at this point. The upper plots show the probability density functions of the distribution of acquirer-target sales differences for the two deal types. While the distribution of absolute differences for cross-border deals seems to lie to the right of the line for national deals in the left plot, the picture next to it draws the graphs for the differences in z-scores. After accounting for industry and country effects, the peaks of the two distributions are very close to each other. The acquirer-target differences are more heterogeneous in cross-border acquisitions than for domestic deals. The distribution of national deals has a higher peakedness, while at both sides the distribution for cross-border deals lies above the graph of national deals. The lower two pictures plot the same two graphs for labor productivity differences. Both distributions are closer around zero, however, there are even more national deals in which firms of similar productivity participate.

Concluding, the results for the performance measures in levels suggest that there is a positive performance difference for acquirers in both types of deals. Hence, “high buys less high” is true with this respect. The performance distance is larger for cross-border deals, in particular in related acquisitions within industries. On the other hand, national acquirers and targets are more similar to each other when performance changes are considered, which would argue for “like buys like” as more characteristic for within country acquisitions. Despite the performance advantage of acquirers on average and in many dimensions, the heterogeneity in the match of acquirer and target firms is large.

4.7 Conclusion

Using a European firm-level dataset in combination with a global M&A database, I analyze the complete sorting of acquirers and targets and compare the ranking for national and cross-border acquisitions. I find the following sorting pattern:

[11] I do not perform Kolmogorov-Smirnov tests on stochastic dominance in addition to the t-tests, as the visual inspection of the data reveals that for almost all differences in performance measures, the cumulative distributions functions of the two acquisition types intersect. In such cases, the Kolmogorov-Smirnov test statistics are not meaningful.

cross-border acquirers are on average larger and more productive than target firms and those are again better than domestic firms not involved in any acquisition even after correcting for industry composition and year effects. The ranking of acquirer and target firms holds also for national deals, but on a lower level. The result is robust across industries and type of deals. Thus, both firm selection into M&A activity and cherry-picking of better than average targets hold simultaneously in this dataset of acquisitions in the European Union.

Further, I discuss the distribution of the performance differences between acquirers and their specific target firms. I find that the differences between acquirers and targets are quite heterogeneous when I link the firms of each deal directly. Using various performance measures, larger and more productive firms acquire smaller firms. The distribution of acquirer-target differences is more concentrated around zero for domestic deals, while size differences in cross-border M&As appear to be more heterogeneous and are also more often positive than in national acquisitions. The results suggest that the question of who buys who is thus answered best with "high buys less high" for cross-border acquisitions, while "like buys like" is more typical for national deals. Although it seems to be more frequent in international M&A deals that efficient firms pick less efficient, but above-average performing targets, there is large heterogeneity in the matches of acquirer and target firms.

Table 4.1
Stylized structure of the combined dataset.

Acquirer ID	Target ID	Control ID	Year	Acquisition Year	Cross-border deal	Acquirer sales	Target Sales	Control Sales
ac 1	ta 1	.	2000	2003	1	20	.	.
ac 1	ta 1	.	2001	2003	1	22	12	.
ac 1	ta 1	.	2002	2003	1	21	9	.
ac 1	ta 1	.	2003	2003	1	23	10	.
ac 1	ta 1	.	2004	2003	1	26	15	.
ac 1	ta 1	.	2005	2003	1	25	14	.
ac 1	ta 1	.	2006	2003	1	.	15	.
ac 1	ta 1	.	2007	2003	1	.	.	.
ac 2	ta 2	.	2000	2006	0	17	.	.
ac 2	ta 2	.	2001	2006	0	16	.	.
ac 2	ta 2	.	2002	2006	0	18	7	.
ac 2	ta 2	.	2003	2006	0	15	5	.
ac 2	ta 2	.	2004	2006	0	.	6	.
ac 2	ta 2	.	2005	2006	0	17	5	.
ac 2	ta 2	.	2006	2006	0	18	6	.
ac 2	ta 2	.	2007	2006	0	17	6	.
.	.	c 1	2000	.	.	.	.	3
.	.	c 1	2001	.	.	.	.	4
.	.	c 1	2002	.	.	.	.	2
.	.	c 1	2003	.	.	.	.	5
.	.	c 1	2004	.	.	.	.	4
.	.	c 1	2005	.	.	.	.	3
.	.	c 1	2006	.	.	.	.	3
.	.	c 1	2007	.	.	.	.	2

"." denotes missing values; the gray lines indicate the year of the merger t, the light gray lines illustrate the pre-acquisition years $t-1$

Table 4.2
Yearly composition of the sample.

Year	Control firms	Cross-border acquirer	Cross-border target	National acquirer	National target	Total
2001	6,092	34	34	228	226	6,614
2002	5,804	49	48	272	263	6,436
2003	7,038	56	49	296	292	7,731
2004	8,034	77	80	405	396	8,992
2005	8,253	101	103	440	433	9,330
2006	9,485	121	121	486	470	10,683
2007	8,652	44	43	161	157	9,057
Total	53,358	482	478	2,288	2,237	58,843

Table 4.3
Country composition of the sample.

Country		Control firms	Cross-border acquirer	Cross-border target	National acquirer	National target	Total
AT	(Austria)	192	8	3	4	4	211
BE	(Belgium)	2,514	40	30	96	93	2,773
BG	(Bulgaria)	67	0	5	8	8	88
CZ	(Czech Republic)	911	12	10	28	24	985
DE	(Germany)	2,156	58	28	93	87	2,422
DK	(Denmark)	979	29	19	37	33	1,097
EE	(Estonia)	671	8	19	29	27	754
ES	(Spain)	10,727	55	61	451	452	11,746
FI	(Finland)	6,818	65	23	271	265	7,442
FR	(France)	16,056	86	95	596	590	17,423
GB	(United Kingdom)	2,079	19	46	198	185	2,527
GR	(Greece)	1,196	10	1	45	39	1,291
HU	(Hungary)	56	1	3	0	0	60
IE	(Ireland)	60	0	0	0	0	60
IT	(Italy)	2,224	53	25	131	128	2,561
LT	(Lithuania)	113	2	7	1	1	124
LV	(Latvia)	361	1	14	12	14	402
NL	(Netherlands)	196	2	6	3	2	209
NO	(Norway)	2,823	19	20	143	143	3,148
PL	(Poland)	1,633	11	33	110	107	1,894
PT	(Portugal)	548	3	9	7	7	574
RO	(Romania)	796	0	14	24	27	861
SI	(Slovenia)	29	0	0	0	0	29
SK	(Slovakia)	152	0	7	1	1	161
Total		53,358	482	478	2,288	2,237	58,843

Table 4.4
Top ten country pairs of cross-border acquisitions.

Country pair Acquirer	Target	Number of cross-border deals	Percent of all deals
ES	FR	22	4.92
FR	ES	18	4.03
FR	GB	18	4.03
BE	FR	16	3.58
IT	ES	16	3.58
IT	FR	15	3.36
FR	BE	14	3.13
FI	EE	13	2.91
DE	FR	11	2.46
FI	NO	11	2.46

Figure 4.1
Regional distribution of deals.

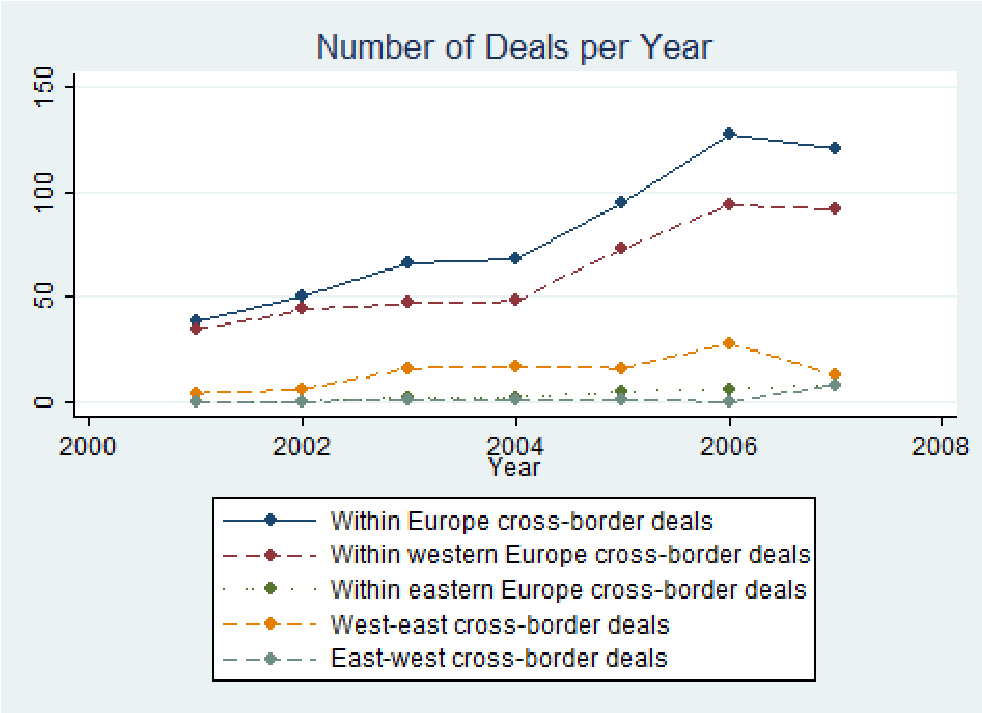

Table 4.5
Industry composition of the sample (NACE 2 digit).

Industry Code	Control firms	Cross-border acquirer	Cross-border target	National acquirer	National target	Total
15	3,702	35	29	150	155	4,071
16	5	0	0	0	0	5
17	397	2	3	16	12	430
18	257	0	1	17	12	287
19	90	0	0	3	3	96
20	806	0	2	15	18	841
21	681	10	7	14	16	728
22	1,836	10	10	91	68	2,015
23	102	2	1	5	2	112
24	1,843	36	25	65	43	2,012
25	1,124	15	13	30	26	1,208
26	1,155	6	15	54	49	1,279
27	749	10	10	24	23	816
28	2,051	19	19	42	57	2,188
29	1,778	33	25	55	59	1,950
30	109	1	4	1	3	118
31	655	5	6	22	19	707
32	642	11	4	19	26	702
33	605	4	8	19	25	661
34	372	2	3	8	7	392
35	531	2	3	18	9	563
36	520	3	4	20	23	570
37	136	0	0	6	7	149
40	894	12	12	46	38	1,002
41	131	0	0	9	7	147
45	3,265	23	16	181	155	3,640

Table 4.6
Industry composition of the sample (NACE 2 digit) – continued.

Industry Code	Control firms	Cross-border acquirer	Cross-border target	National acquirer	National target	Total
50	1,285	6	10	52	48	1,401
51	5,887	61	74	274	264	6,560
52	1,940	6	11	55	93	2,105
55	614	3	8	18	25	668
60	1,145	3	8	56	67	1,279
61	245	4	0	15	8	272
62	104	0	1	4	6	115
63	1,298	8	5	80	64	1,455
64	863	9	14	68	53	1,007
70	1,100	13	10	58	53	1,234
71	321	8	1	36	27	393
72	3,421	44	38	253	262	4,018
73	223	6	2	6	12	249
74	8,289	58	59	267	265	8,938
80	139	2	1	8	8	158
85	788	2	1	43	49	883
90	266	0	1	13	11	291
92	809	7	11	44	46	917
93	185	1	3	8	14	211
Total	53,358	482	478	2,288	2,237	58,843

Figure 4.2
Related and unrelated deals.

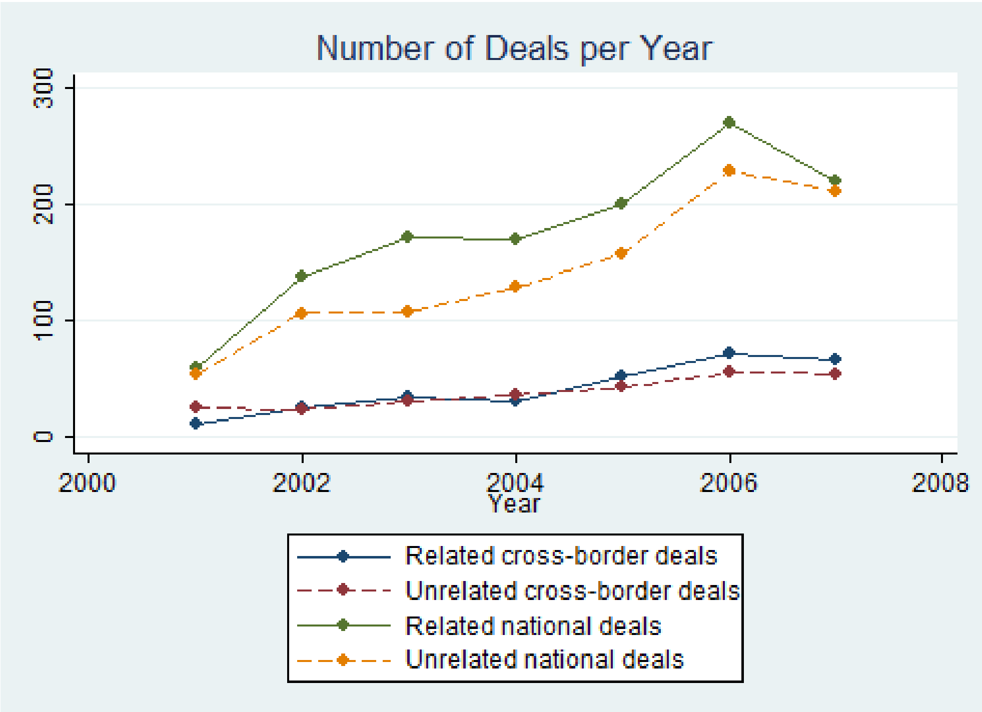

Figure 4.3
Regional distribution of related and unrelated deals.

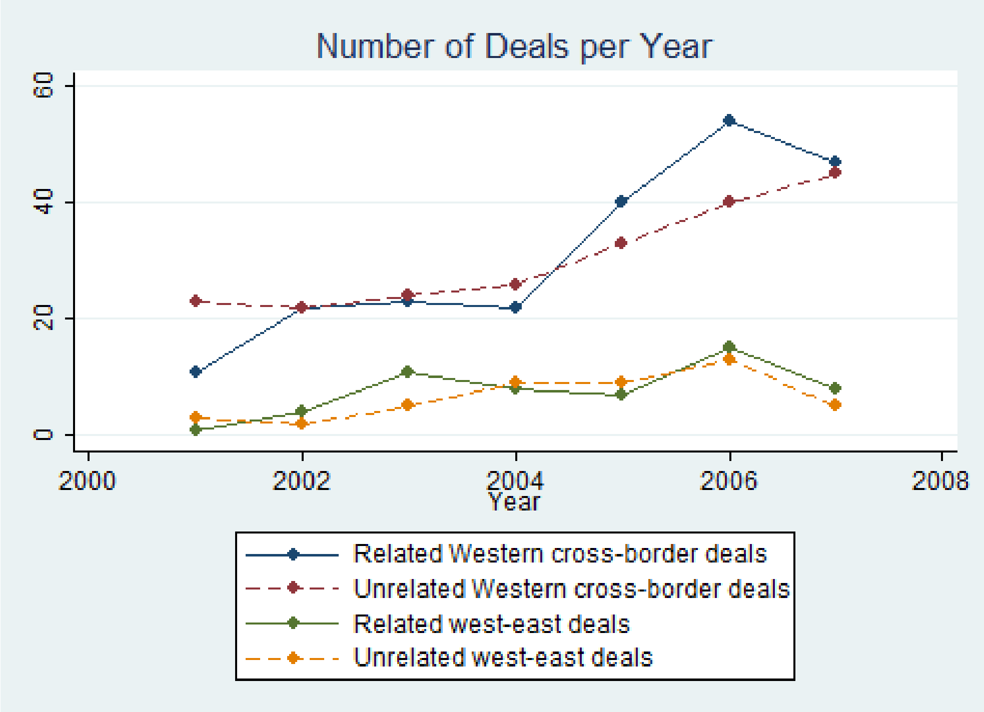

Table 4.7

Descriptive statistics of the sample – levels.

	Cross-border Acquirer		National Acquirer		Cross-border Target		National Target		Control Firm	
	$\bar{x}$	s_x	$\bar{x}$	s_x	$\bar{x}$	s_x	$\bar{x}$	s_x	$\bar{x}$	s_x
Means and standard errors of the untransformed variables										
Log sales	11.410	(2.086)	10.514	(1.995)	9.461	(1.710)	8.913	(1.678)	6.962	(1.881)
Log capital	8.969	(2.699)	7.977	(2.608)	6.924	(2.501)	6.214	(2.474)	4.432	(2.363)
Log labor	5.689	(2.030)	5.156	(1.916)	4.265	(1.594)	3.782	(1.568)	2.173	(1.541)
Log labor productivity	5.721	(1.178)	5.358	(1.106)	5.196	(1.113)	5.132	(1.073)	4.790	(1.096)
Log capital intensity	3.280	(1.746)	2.821	(1.838)	2.659	(1.794)	2.432	(1.885)	2.260	(1.749)
Log TFP	0.357	(1.057)	0.192	(0.896)	0.190	(0.921)	0.107	(0.863)	-0.133	(0.902)
N	482		2,288		478		2,237		53,358	
Means and standard errors of the z-scores										
Log sales	2.826	(1.714)	2.476	(1.580)	1.571	(1.288)	1.419	(1.201)	0.029	(0.973)
Log capital	2.288	(1.473)	1.945	(1.371)	1.223	(1.308)	1.039	(1.252)	0.020	(0.977)
Log labor	2.687	(1.708)	2.460	(1.702)	1.569	(1.661)	1.395	(1.331)	0.027	(0.976)
Log labor productivity	1.008	(1.698)	0.663	(1.202)	0.568	(1.538)	0.435	(1.199)	0.011	(0.967)
Log capital intensity	0.602	(1.213)	0.370	(1.142)	0.340	(1.192)	0.125	(1.239)	0.002	(0.973)
Log TFP	0.707	(1.584)	0.431	(1.163)	0.415	(1.405)	0.342	(1.319)	0.010	(0.966)
N	392		1,947		375		1,912		51,697	

Table 4.8
Descriptive statistics of the sample – growth rates.

	Cross-border Acquirer		National Acquirer		Cross-border Target		National Target		Control Firm	
	$\bar{x}$	s_x	$\bar{x}$	s_x	$\bar{x}$	s_x	$\bar{x}$	s_x	$\bar{x}$	s_x
Means and standard errors of the untransformed variables										
Change log sales	0.069	(0.482)	0.092	(0.458)	0.048	(0.316)	0.050	(0.421)	0.035	(0.432)
Change log capital	0.015	(0.577)	0.031	(0.638)	-0.085	(0.574)	-0.063	(0.553)	-0.000	(0.618)
Change log labor	0.034	(0.378)	0.068	(0.453)	0.003	(0.313)	0.007	(0.445)	0.023	(0.372)
Change log labor productivity	0.035	(0.442)	0.023	(0.520)	0.045	(0.408)	0.043	(0.521)	0.012	(0.499)
Change log capital intensity	-0.019	(0.512)	-0.038	(0.685)	-0.088	(0.625)	-0.070	(0.633)	-0.023	(0.684)
Change log TFP	0.008	(0.456)	0.009	(0.491)	0.041	(0.415)	0.039	(0.495)	-0.008	(0.480)
N	364		1,773		351		1,697		37,725	
Means and standard errors of the z-scores										
Change log sales	0.117	(1.974)	0.128	(1.724)	-0.066	(1.482)	-0.010	(1.259)	-0.042	(0.903)
Change log capital	0.053	(1.280)	0.111	(1.411)	-0.131	(1.545)	-0.078	(1.361)	-0.008	(0.955)
Change log labor	0.165	(1.818)	0.146	(2.617)	-0.002	(3.111)	0.145	(5.146)	-0.015	(0.953)
Change log labor productivity	0.058	(1.245)	0.054	(1.571)	-0.049	(1.356)	0.040	(1.447)	-0.013	(0.942)
Change log capital intensity	0.037	(1.110)	0.034	(1.447)	-0.200	(1.720)	-0.027	(1.397)	0.001	(0.973)
Change log TFP	0.087	(1.544)	0.062	(1.877)	0.078	(2.308)	0.111	(1.611)	-0.000	(0.974)
N	274		1,333		260		1,263		35,080	

Table 4.9
OLS regressions of the performance measures on group dummies.

	Log sales		Log capital		Log labor		Log labor productivity		Log capital intensity		Log TFP	
Estimated coefficients and standard errors												
Cross-border acquirer	3.664***	(0.091)	3.722***	(0.109)	2.984***	(0.089)	0.680***	(0.054)	0.738***	(0.073)	0.506***	(0.049)
Cross-border target	1.933***	(0.073)	1.851***	(0.097)	1.544***	(0.066)	0.389***	(0.046)	0.307***	(0.073)	0.316***	(0.043)
National acquirer	3.025***	(0.040)	3.006***	(0.049)	2.577***	(0.039)	0.448***	(0.022)	0.429***	(0.035)	0.341***	(0.020)
National target	1.633***	(0.033)	1.466***	(0.045)	1.354***	(0.031)	0.279***	(0.021)	0.112***	(0.035)	0.247***	(0.019)
Constant	8.070***	(0.048)	6.062***	(0.061)	3.119***	(0.041)	4.951***	(0.028)	2.943***	(0.046)	-0.209***	(0.026)
Test of equality of coefficients and p-values												
Cross-border acquirer = cross-border target	1.731	0.000	1.871	0.000	1.439	0.000	0.292	0.000	0.432	0.000	0.189	0.004
National acquirer = national target	1.392	0.000	1.540	0.000	1.223	0.000	0.169	0.000	0.317	0.000	0.094	0.000
Cross-border acquirer = national acquirer	0.639	0.000	0.716	0.000	0.407	0.000	0.232	0.000	0.309	0.000	0.165	0.002
Cross-border target = national target	0.300	0.000	0.385	0.000	0.190	0.008	0.110	0.027	0.194	0.016	0.070	0.132
National acquirer = cross-border target	1.092	0.000	1.155	0.000	1.033	0.000	0.059	0.236	0.122	0.126	0.024	0.604
Industry, country, time dummies	Yes		Yes		Yes		Yes		Yes		Yes	
N	58,843		58,843		58,843		58,843		58,843		58,843	
Adjusted R^2	0.427		0.400		0.402		0.266		0.202		0.020	

Table 4.10
OLS regressions of the different growth measures on group dummies.

	Log growth sales		Log growth capital		Log growth labor		Log growth labor productivity		Log growth capital intensity		Log growth TFP	
Estimated coefficients and standard errors												
Cross-border acquirer	0.069**	(0.030)	0.054	(0.036)	0.051**	(0.026)	0.014	(0.022)	0.018	(0.027)	0.016	(0.024)
Cross-border target	-0.004	(0.022)	-0.079***	(0.030)	0.002	(0.018)	-0.010	(0.024)	-0.063*	(0.033)	0.046**	(0.022)
National acquirer	0.094***	(0.014)	0.064***	(0.015)	0.073***	(0.012)	0.023*	(0.013)	0.003	(0.018)	0.019	(0.012)
National target	0.002	(0.010)	-0.046***	(0.012)	-0.004	(0.010)	0.010	(0.012)	-0.043***	(0.016)	0.048***	(0.012)
Constant	0.025*	(0.015)	0.001	(0.019)	0.041***	(0.013)	-0.031*	(0.017)	-0.053**	(0.024)	-0.086***	(0.019)
Test of equality of coefficients and p-values												
Cross-border acquirer = cross-border target	0.074	0.045	0.132	0.004	0.049	0.113	0.025	0.452	0.081	0.058	-0.030	0.350
National acquirer = national target	0.093	0.000	0.110	0.000	0.077	0.000	0.013	0.448	0.046	0.046	-0.029	0.085
Cross-border acquirer = national acquirer	-0.025	0.445	-0.011	0.780	-0.022	0.437	-0.009	0.724	0.015	0.639	-0.003	0.913
Cross-border target = national target	-0.006	0.797	-0.033	0.302	0.006	0.770	-0.021	0.445	-0.020	0.579	-0.001	0.957
National acquirer = cross-border target	0.099	0.000	0.143	0.000	0.071	0.001	0.034	0.221	0.066	0.075	-0.028	0.271
Industry, country, time dummies	Yes		Yes		Yes		Yes		Yes		Yes	
N	58,843		56,345		54,123		54,123		42,117		41,910	
Adjusted R^2	0.010		0.007		0.004		0.005		0.006		0.004	

Table 4.11

OLS regressions of the performance measures on group dummies – Related deals.

	Log sales		Log capital		Log labor		Log labor productivity		Log capital intensity		Log TFP	
Estimated coefficients and standard errors												
Cross-border acquirer	3.932***	(0.116)	4.061***	(0.139)	3.221***	(0.117)	0.711***	(0.074)	0.840***	(0.099)	0.513***	(0.067)
Cross-border target	2.071***	(0.096)	2.002***	(0.128)	1.678***	(0.088)	0.393***	(0.060)	0.324***	(0.096)	0.315***	(0.055)
National acquirer	3.115***	(0.049)	3.040***	(0.060)	2.697***	(0.048)	0.418***	(0.026)	0.343***	(0.043)	0.329***	(0.024)
National target	1.659***	(0.042)	1.424***	(0.057)	1.382***	(0.040)	0.277***	(0.026)	0.042	(0.043)	0.258***	(0.024)
Constant	8.082***	(0.049)	6.058***	(0.063)	3.131***	(0.041)	4.951***	(0.028)	2.927***	(0.047)	-0.204***	(0.027)
Test of equality of coefficients and p-values												
Cross-border acquirer = cross-border target	1.862	0.000	2.059	0.000	1.543	0.000	0.319	0.001	0.516	0.000	0.198	0.021
National acquirer = national target	1.457	0.000	1.616	0.000	1.315	0.000	0.142	0.000	0.301	0.000	0.070	0.034
Cross-border acquirer = national acquirer	0.817	0.000	1.022	0.000	0.524	0.000	0.293	0.000	0.497	0.000	0.185	0.009
Cross-border target = national target	0.412	0.000	0.578	0.000	0.296	0.002	0.116	0.076	0.282	0.007	0.057	0.337
National acquirer = cross-border target	1.045	0.000	1.038	0.000	1.019	0.000	0.026	0.694	0.019	0.855	0.013	0.823
Industry, country, time dummies	Yes		Yes		Yes		Yes		Yes		Yes	
N	56,521		56,521		56,521		56,521		56,521		56,521	
Adjusted R^2	0.395		0.377		0.373		0.265		0.200		0.017	

Table 4.12
OLS regressions of the performance measures on group dummies – Unrelated deals.

	Log sales		Log capital		Log labor		Log labor productivity		Log capital intensity		Log TFP	
Estimated coefficients and standard errors												
Cross-border acquirer	3.315***	(0.140)	3.294***	(0.168)	2.676***	(0.133)	0.639***	(0.077)	0.618***	(0.105)	0.491***	(0.073)
Cross-border target	1.736***	(0.111)	1.646***	(0.146)	1.357***	(0.098)	0.379***	(0.069)	0.289***	(0.112)	0.312***	(0.067)
National acquirer	2.873***	(0.066)	2.934***	(0.079)	2.386***	(0.066)	0.487***	(0.035)	0.548***	(0.056)	0.356***	(0.033)
National target	1.578***	(0.053)	1.507***	(0.069)	1.299***	(0.047)	0.279***	(0.033)	0.208***	(0.057)	0.227***	(0.031)
Constant	8.056***	(0.050)	6.012***	(0.063)	3.132***	(0.041)	4.924***	(0.029)	2.880***	(0.047)	-0.222***	(0.027)
Test of equality of coefficients and p-values												
Cross-border acquirer = cross-border target	1.578	0.000	1.648	0.000	1.318	0.000	0.260	0.012	0.329	0.031	0.179	0.068
National acquirer = national target	1.295	0.000	1.427	0.000	1.087	0.000	0.209	0.000	0.340	0.000	0.128	0.003
Cross-border acquirer = national acquirer	0.441	0.004	0.360	0.052	0.290	0.049	0.151	0.072	0.070	0.553	0.136	0.085
Cross-border target = national target	0.158	0.194	0.139	0.387	0.058	0.592	0.100	0.190	0.081	0.517	0.085	0.246
National acquirer = cross-border target	1.137	0.000	1.288	0.000	1.028	0.000	0.109	0.161	0.259	0.036	0.044	0.555
Industry, country, time dummies	Yes		Yes		Yes		Yes		Yes		Yes	
N	55,680		55,680		55,680		55,680		55,680		55,680	
Adjusted R^2	0.370		0.360		0.344		0.261		0.193		0.017	

Table 4.13

OLS regressions of the different growth measures on group dummies – Related deals.

	Log growth sales		Log growth capital		Log growth labor		Log growth labor productivity		Log growth capital intensity		Log growth TFP	
Estimated coefficients and standard errors												
Cross-border acquirer	0.049	(0.030)	0.070	(0.046)	0.040*	(0.022)	0.017	(0.028)	0.022	(0.029)	0.003	(0.026)
Cross-border target	0.015	(0.030)	-0.095***	(0.033)	0.010	(0.023)	-0.005	(0.028)	-0.096**	(0.041)	0.035	(0.026)
National acquirer	0.088***	(0.018)	0.078***	(0.019)	0.079***	(0.014)	0.009	(0.015)	0.004	(0.022)	-0.000	(0.015)
National target	-0.012	(0.011)	-0.058***	(0.016)	-0.018	(0.013)	0.015	(0.015)	-0.045**	(0.020)	0.043***	(0.015)
Constant	0.030**	(0.015)	0.012	(0.019)	0.040***	(0.013)	-0.023	(0.017)	-0.079***	(0.024)	-0.095***	(0.020)
Test of equality of coefficients and p-values												
Cross-border acquirer = cross-border target	0.033	0.429	0.165	0.003	0.030	0.334	0.021	0.586	0.118	0.017	-0.032	0.380
National acquirer = national target	0.100	0.000	0.136	0.000	0.097	0.000	-0.006	0.769	0.049	0.089	-0.044	0.034
Cross-border acquirer = national acquirer	-0.040	0.246	-0.009	0.862	-0.039	0.127	0.008	0.796	0.018	0.600	0.004	0.903
Cross-border target = national target	0.027	0.387	-0.038	0.296	0.028	0.292	-0.019	0.540	-0.051	0.264	-0.008	0.782
National acquirer = cross-border target	0.073	0.034	0.174	0.000	0.069	0.010	0.013	0.677	0.100	0.030	-0.036	0.224
Industry, country, time dummies	Yes		Yes		Yes		Yes		Yes		Yes	
N	56,521		54,096		51,892		51,892		40,400		40,209	
Adjusted R^2	0.009		0.007		0.004		0.005		0.005		0.004	

Table 4.14

OLS regressions of the different growth measures on group dummies – Unrelated deals.

	Log growth sales		Log growth capital		Log growth labor		Log growth labor productivity		Log growth capital intensity		Log growth TFP	
Estimated coefficients and standard errors												
Cross-border acquirer	0.094*	(0.055)	0.031	(0.054)	0.064	(0.050)	0.012	(0.035)	0.014	(0.050)	0.033	(0.043)
Cross-border target	-0.029	(0.031)	-0.061	(0.052)	-0.009	(0.027)	-0.018	(0.042)	-0.023	(0.053)	0.060	(0.038)
National acquirer	0.102***	(0.020)	0.043*	(0.024)	0.063***	(0.019)	0.045**	(0.023)	0.003	(0.029)	0.048**	(0.020)
National target	0.021	(0.017)	-0.028	(0.020)	0.015	(0.015)	0.004	(0.019)	-0.038	(0.024)	0.054***	(0.021)
Constant	0.029*	(0.015)	0.000	(0.020)	0.044***	(0.013)	-0.028	(0.018)	-0.086***	(0.024)	-0.019	(0.020)
Test of equality of coefficients and p-values												
Cross-border acquirer = cross-border target	0.124	0.049	0.092	0.221	0.073	0.200	0.029	0.590	0.037	0.611	-0.027	0.643
National acquirer = national target	0.082	0.002	0.072	0.019	0.048	0.046	0.041	0.166	0.041	0.271	-0.007	0.816
Cross-border acquirer = national acquirer	-0.008	0.888	-0.012	0.839	0.001	0.987	-0.033	0.426	0.011	0.852	-0.015	0.755
Cross-border target = national target	-0.050	0.156	-0.032	0.559	-0.024	0.441	-0.022	0.631	0.015	0.800	0.006	0.899
National acquirer = cross-border target	0.132	0.000	0.104	0.069	0.072	0.029	0.063	0.185	0.026	0.663	-0.012	0.779
Industry, country, time dummies	Yes		Yes		Yes		Yes		Yes		Yes	
N	55,680		53,239		51,064		51,064		39,615		39,426	
Adjusted R^2	0.009		0.007		0.003		0.005		0.005		0.004	

Table 4.15
Kolmogorov-Smirnov test on stochastic dominance of distributions (z-scores) – levels.

	Cross-border acquirer $\succ$ national acquirer	Cross-border target $\succ$ national target	Cross-border acquirer $\succ$ cross-border target	National acquirer $\succ$ national target	National acquirer $\succ$ cross-border target	National target $\succ$ domestic firm
Log sales						
D statistic two-sided	0.131	0.086	0.387	0.333	0.271	0.506
p-value two-sided	0.000	0.015	0.000	0.000	0.000	0.000
D statistic one-sided	-0.013	-0.017	0.000	-0.000	-0.002	-0.001
p-value one-sided	0.901	0.839	1.000	1.000	0.999	0.999
Log capital						
D statistic two-sided	0.140	0.090	0.395	0.318	0.260	0.356
p-value two-sided	0.000	0.010	0.000	0.000	0.000	0.000
D statistic one-sided	-0.002	-0.006	0.000	-0.001	-0.000	-0.002
p-value one-sided	0.997	0.975	1.000	0.999	1.000	0.986
Log labor						
D statistic two-sided	0.104	0.059	0.370	0.323	0.287	0.479
p-value two-sided	0.001	0.202	0.000	0.000	0.000	0.000
D statistic one-sided	-0.005	-0.021	-0.008	-0.000	-0.006	-0.001
p-value one-sided	0.981	0.748	0.976	1.000	0.974	0.993

Table 4.16
Kolmogorov-Smirnov test on stochastic dominance of distributions (z-scores) – levels continued.

	Cross-border acquirer $\succ$ national acquirer	Cross-border target $\succ$ national target	Cross-border acquirer $\succ$ cross-border target	National acquirer $\succ$ national target	National acquirer $\succ$ cross-border target	National target $\succ$ domestic firm
Log labor productivity						
D statistic two-sided	0.132	0.108	0.131	0.107	0.060	0.178
p-value two-sided	0.000	0.001	0.002	0.000	0.180	0.000
D statistic one-sided	-0.016	-0.021	0.000	-0.003	-0.022	-0.002
p-value one-sided	0.843	0.761	1.000	0.987	0.745	0.990
Log capital intensity						
D statistic two-sided	0.137	0.111	0.143	0.113	0.054	0.046
p-value two-sided	0.000	0.001	0.000	0.000	0.284	0.001
D statistic one-sided	-0.010	-0.006	-0.010	-0.002	-0.026	-0.007
p-value one-sided	0.936	0.976	0.962	0.993	0.642	0.822
Log TFP						
D statistic two-sided	0.098	0.089	0.099	0.045	0.069	0.133
p-value two-sided	0.003	0.011	0.040	0.034	0.088	0.000
D statistic one-sided	-0.008	-0.039	-0.005	-0.005	-0.069	-0.004
p-value one-sided	0.958	0.382	0.990	0.947	0.050	0.930

Table 4.17
Kolmogorov-Smirnov test on stochastic dominance of distributions (z-scores) – growth rates.

	Cross-border acquirer $\succ$ national acquirer	Cross-border target $\succ$ national target	Cross-border acquirer $\succ$ cross-border target	National acquirer $\succ$ national target	National acquirer $\succ$ cross-border target	National target $\succ$ domestic firm
Log growth sales						
D statistic two-sided	0.035	0.071	0.069	0.099	0.064	0.031
p-value two-sided	0.806	0.079	0.297	0.032	0.000	0.077
D statistic one-sided	-0.034	-0.034	-0.012	-0.004	-0.004	-0.024
p-value one-sided	0.480	0.481	0.942	0.966	0.991	0.135
Log growth capital						
D statistic two-sided	0.036	0.047	0.140	0.124	0.127	0.027
p-value two-sided	0.792	0.488	0.001	0.000	0.000	0.190
D statistic one-sided	-0.024	-0.033	-0.012	-0.003	-0.010	-0.027
p-value one-sided	0.691	0.521	0.949	0.982	0.944	0.100
Log growth labor						
D statistic two-sided	0.052	0.049	0.061	0.081	0.085	0.033
p-value two-sided	0.365	0.465	0.493	0.000	0.027	0.066
D statistic one-sided	-0.052	-0.029	-0.021	-0.044	-0.016	-0.033
p-value one-sided	0.198	0.613	0.857	0.934	0.982	0.035

Table 4.18
Kolmogorov-Smirnov test on stochastic dominance of distributions (z-scores) – growth rates continued.

	Cross-border acquirer $\succ$ national acquirer	Cross-border target $\succ$ national target	Cross-border acquirer $\succ$ cross-border target	National acquirer $\succ$ national target	National acquirer $\succ$ cross-border target	National target $\succ$ domestic firm
Log growth labor productivity						
D statistic two-sided	0.057	0.059	0.080	0.045	0.050	0.045
p-value two-sided	0.252	0.243	0.177	0.065	0.425	0.003
D statistic one-sided	-0.020	-0.022	-0.052	-0.008	-0.048	-0.045
p-value one-sided	0.786	0.755	0.380	0.908	0.255	0.002
Log growth capital intensity						
D statistic two-sided	0.056	0.038	0.138	0.099	0.098	0.033
p-value two-sided	0.415	0.875	0.007	0.000	0.019	0.110
D statistic one-sided	-0.034	-0.038	-0.041	-0.008	-0.024	-0.033
p-value one-sided	0.579	0.512	0.624	0.925	0.767	0.059
Log growth TFP						
D statistic two-sided	0.095	0.062	0.075	0.037	0.091	0.066
p-value two-sided	0.025	0.327	0.387	0.317	0.041	0.000
D statistic one-sided	-0.024	-0.009	-0.075	-0.037	-0.091	-0.020
p-value one-sided	0.770	0.968	0.216	0.168	0.024	0.382

Figure 4.4
Cumulative distribution functions.

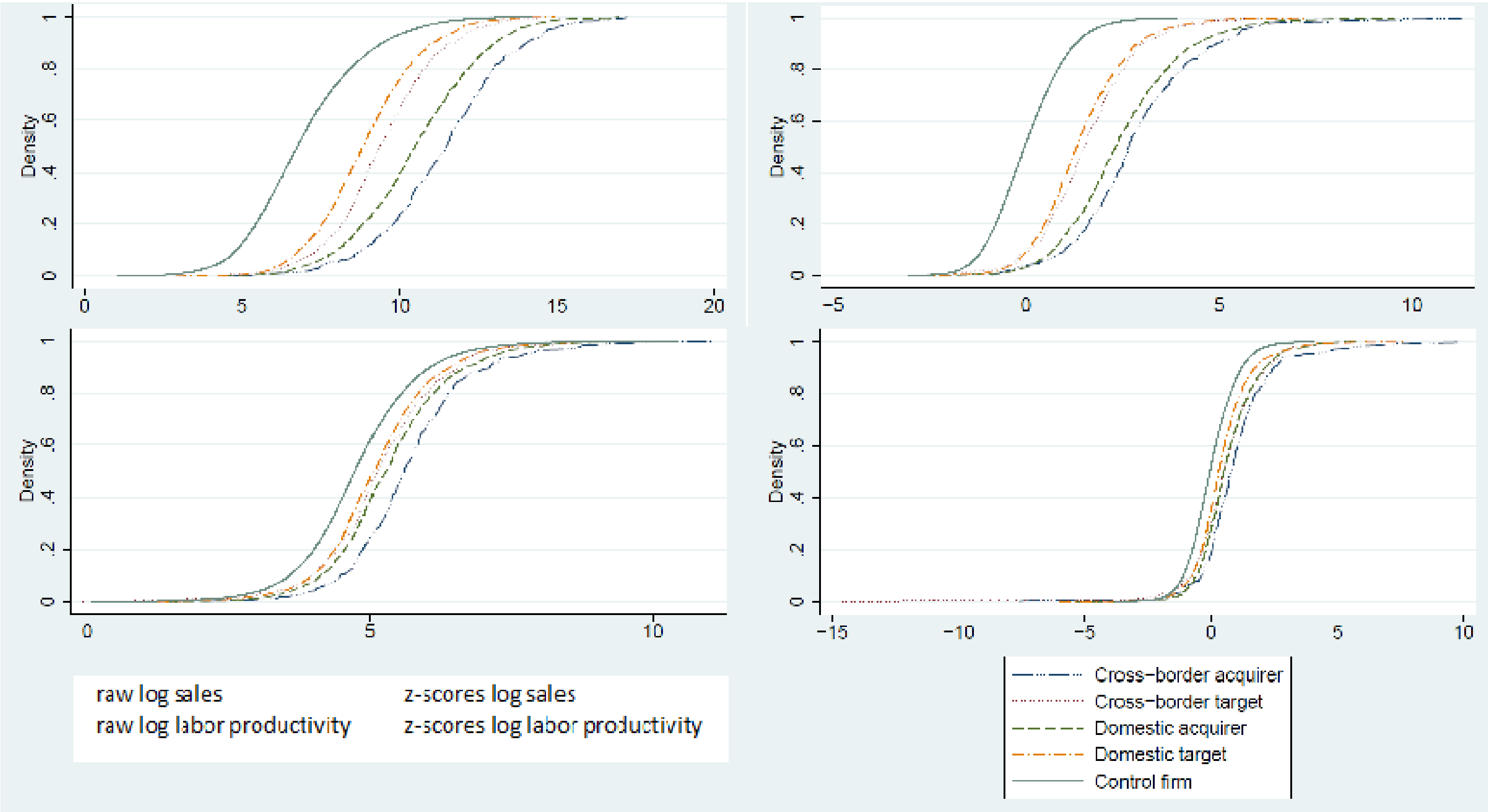

Table 4.19

Descriptive statistics of the acquirer-target level differences.

	Cross-border acquisitions					National acquisitions				
	$\bar{x}$	s_x	$p25$	$p50$	$p75$	$\bar{x}$	s_x	$p25$	$p50$	$p75$
Absolute difference in the untransformed variables										
Log sales	2.008	(2.213)	0.588	2.067	3.445	1.573	(2.069)	0.343	1.561	2.833
Log capital	2.135	(2.865)	0.359	1.938	3.862	1.744	(2.663)	0.182	1.730	3.395
Log labor	1.448	(2.259)	0.012	1.343	2.895	1.365	(2.100)	0.105	1.342	2.657
Log labor productivity	0.560	(1.451)	-0.248	0.445	1.257	0.208	(1.1 82)	-0.348	0.178	0.742
Log capital intensity	0.687	(1.950)	-0.527	0.555	1.785	0.379	(1.896)	-0.692	0.329	1.427
Log TFP	0.176	(1.309)	-0.559	0.032	0.761	0.075	(1.119)	-0.516	0.047	0.634
N	447					2,137				
Difference in z-scores										
Log sales	1.159	(1.940)	0.040	1.074	2.257	1.067	(1.604)	0.160	0.989	1.894
Log capital	1.008	(1.698)	-0.107	1.029	2.042	0.912	(1.577)	0.010	0.894	1.822
Log labor	1.021	(2.360)	-0.164	1.144	2.418	1.081	(1.832)	0.027	1.057	2.136
Log labor productivity	0.393	(2.250)	-0.642	0.238	1.150	0.209	(1.437)	-0.484	0.187	0.887
Log capital intensity	0.267	(1.546)	-0.556	0.265	1.061	0.226	(1.419)	-0.533	0.186	0.939
Log TFP	0.242	(2.045)	-0.793	0.083	1.158	0.079	(1.605)	-0.664	0.070	0.863
N	289					1,728				

Table 4.20
Descriptive statistics of the acquirer-target growth differences.

	Cross-border acquisitions					National acquisitions				
	$\bar{x}$	s_x	$p25$	$p50$	$p75$	$\bar{x}$	s_x	$p25$	$p50$	$p75$
Absolute difference in the untransformed variables										
Log growth sales	0.019	(0.578)	-0.118	0.000	0.205	0.036	(0.605)	-0.140	0.017	0.186
Log growth capital	0.122	(0.834)	-0.151	0.076	0.377	0.095	(0.827)	-0.169	0.076	0.355
Log growth labor	0.025	(0.466)	-0.097	0.019	0.154	0.064	(0.621)	-0.095	0.009	0.189
Log growth labor productivity	-0.006	(0.555)	-0.158	0.013	0.186	-0.028	(0.724)	-0.199	0.000	0.187
Log growth capital intensity	0.097	(0.812)	-0.243	0.090	0.375	0.030	(0.915)	-0.254	0.050	0.357
Log growth TFP	-0.037	(0.587)	-0.231	0.002	0.191	-0.037	(0.686)	-0.226	-0.011	0.188
N	371					1,576				
Difference in z-scores										
Log growth sales	0.115	(2.298)	-0.323	0.035	0.550	0.069	(2.155)	-0.366	0.063	0.487
Log growth capital	0.242	(2.143)	-0.267	0.188	0.808	0.208	(1.896)	-0.374	0.171	0.739
Log growth labor	0.230	(3.246)	-0.405	0.011	0.392	-0.093	(5.896)	-0.355	0.033	0.560
Log growth labor productivity	0.023	(1.279)	-0.379	0.040	0.465	-0.058	(2.087)	-0.417	0.000	0.440
Log growth capital intensity	0.234	(2.154)	-0.407	0.192	0.832	0.077	(1.932)	-0.406	0.113	0.695
Log growth TFP	-0.153	(1.955)	-0.662	0.026	0.558	-0.139	(2.502)	-0.496	-0.002	0.490
N	216					1,057				

Figure 4.5
Probability density functions of acquirer-target differences.

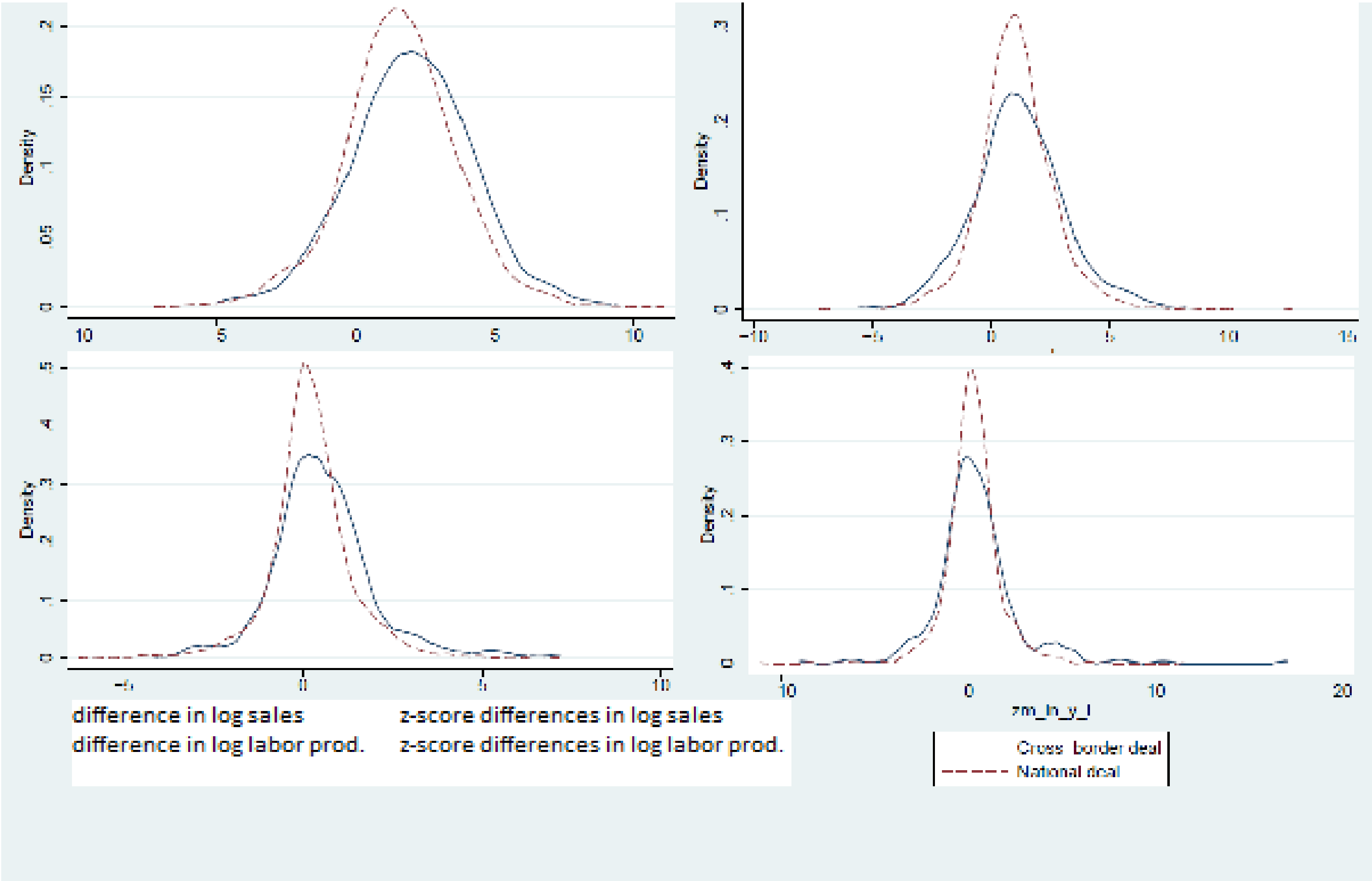

Table 4.21
OLS regressions of the acquirer-target difference on deal type.

	Log sales		Log capital		Log labor		Log labor productivity		Log capital intensity		Log TFP	
Estimated coefficients and standard errors												
Cross-border deal vs. national deals	0.452***	(0.126)	0.420***	(0.159)	0.149	(0.130)	0.303***	(0.083)	0.271**	(0.118)	0.176**	(0.078)
Related cross-border deal vs. related national deals	0.501***	(0.157)	0.572***	(0.202)	0.150	(0.162)	0.351***	(0.102)	0.422***	(0.150)	0.206**	(0.094)
Unrelated cross-border deal vs. unrelated national deals	0.419**	(0.211)	0.187	(0.259)	0.135	(0.214)	0.284**	(0.140)	0.052	(0.201)	0.201	(0.135)
	Log growth sales		Log growth capital		Log growth labor		Log growth labor productivity		Log growth capital intensity		Log growth TFP	
Estimated coefficients and standard errors												
Cross-border deal vs. national deals	-0.021	(0.044)	0.050	(0.052)	-0.009	(0.038)	-0.013	(0.042)	0.072	(0.058)	-0.012	(0.043)
Related cross-border deal vs. related national deals	-0.101*	(0.057)	0.094	(0.064)	-0.063	(0.043)	-0.020	(0.054)	0.126*	(0.070)	-0.010	(0.050)
Unrelated cross-border deal vs. unrelated national deals	0.090	(0.073)	0.044	(0.083)	0.033	(0.068)	0.026	(0.074)	0.042	(0.097)	0.003	(0.081)

Chapter 5

Cultural diversity and plant productivity

5.1 Introduction

International migration has changed the cultural mix of the German population as in many other European societies. Despite its rising importance, the effects of migration on the economy of the host country are still discussed rather controversially. The opening-up of the labor markets to immigrants from eight middle and eastern European countries that joined the European Union in 2004 provided the most recent example for the heated debate on potentially adverse effects of immigration on employment and wages in the central European member countries. Both the economic literature on migration and the public debate appear to be centered around the impact of an increased presence of immigrants on economic outcomes of the native population. Yet there is a second aspect of migration. Immigrants do not form one homogeneous group, but they turn out to be rather diverse in their cultures. Not only do they bring different languages, behaviors, and traditions from their home country, they also add new sets of skills, knowledge, and experiences to their host countries.

As a result, people from different nations interact more frequently with each other in their communities and also at work. In the managerial literature, this rise in (team) diversity is sometimes named a "double-edged sword" (Horwitz & Horwitz, 2007). On the one hand, diversity creates difficulties that would otherwise not be present. Misunderstandings due to language problems increase transaction costs, incompatible expectations reduce productivity at least in the short run and can even lead to team failure. But on the other hand, a diverse ethnic mix also translates into a broader set of interests, perspectives, and abilities that give rise to synergies if they are complementary to each other. Innovative solutions can result from exchanging and combining existing with new ideas, with a positive effect on innovation, business opportunities, and productivity (Lazear, 1999). The question whether the benefits of diversity compensate the associated costs and thus whether the diversification of a country's population with respect to their nationalities has a productivity increasing or a negative effect on productivity in the host country is an empirical one.

We contribute to this discussion and estimate the effects of a culturally diverse workforce on the productivity of German plants in an augmented production function framework. The innovative features of this research contribution are firstly, that we look at the disaggregated level of establishments directly, and secondly, that we try to separate the effects of the establishments' own workforce on its productivity and regional spillover effects that result from the composition of the workforce in the the plants' region. Thirdly, we use System GMM methods to control for the potential endogeneity of the diversity measures due to unobserved influences and productivity shocks at the region-industry or plant level.

The impact of diversity on economic outcomes has been studied in various fields as documented in the comprehensive survey of Alesina & Ferrara (2005). They analyze how the effects of cultural diversity materialize at very different levels or units of observation reaching from the country level to analyses of team performance. A recently growing literature looks at regional effects of diversity. Estimating wage and employment effects on natives, several papers try to assess whether culturally diverse regions benefit from positive consumption and production amenities or whether diversity has a negative impact on regional economic performance (Glaeser et al., 2001; Ottoviano & Peri, 2005; Ottaviano & Peri, 2006; Südekum et al., 2012). The productivity effects found at the region level might have two different sources: via knowledge externalities that materialize at the regional level or directly within the production process.

Our approach thus takes the analysis one step further as we try to distinguish the two potential channels through which a plant's observed productivity could be influenced by a diverse workforce. First, we look at the composition of the workforce of the plant itself, where native and non-native employees interact directly within the unit of production. As Lazear (1999) points out, a necessary condition for a positive effect is that the skill sets of the different group members do not overlap completely. Ottaviano & Peri (2012) find small but positive imperfect substitutability between migrants and natives even within narrowly defined experience and age cells, supporting the view that migrant workers bring new abilities to an establishment.

While there are studies that find a positive effect of racial diversity on team outcomes (for example Richard, 2000; Ellison et al., 2010; Watson et al., 1993), Horwitz & Horwitz (2007) find no clear relation to team performance in a large meta-study. Kahane et al. (2012) shows that teams of the National Hockey League with a high share of foreign players perform better than homogeneous competitors, but he finds that increasing diversity among the foreign members reduces the team outcome due to increased language costs. At the firm level, Parrotta et al. (2010) do not find a significant effect of diversity on firm productivity with Danish data when they instrument the plant-level variables with their regional counterparts. Considering innovation as an alternative measure for firm performance, Chellaraj et al. (2008) find a positive effect of the presence of foreign graduate students on U.S. universities' patenting activities and Ozgen et al. (2011) show that a high share of migrants slightly reduces innovative output, but diversity among migrants increases product innovations of Dutch firms.

Second, we extend the analysis and test whether there is also a spillover effect emerging at the regional level. We ask whether plants benefit from the characteristics of the workforce in the region they are located in given the composition of their own workforce. The mechanisms for efficiency gains might materialize at the regional level if the interaction between people from different backgrounds and resulting synergies generate knowledge spillovers. Similar to Moretti (2004), who shows that firms in regions with a higher share of human capital benefit from knowledge externalities, plants located in regions with a highly diversified workforce might experience productivity increases. In fact, Audretsch et al. (2010) show that technology-oriented start-ups are positively affected by regional diversity and Niebuhr (2010) finds a positive effect on regional R&D in Germany.

With this research, we try to assess the impact of a culturally diverse workforce within plants and regions estimating augmented production functions for a comprehensive sample of German establishments. The survey data is supplemented by detailed administrative employee information that allows the construction of measures of the composition of the plants' workforce as well as of the characteristics of the regions' workforce. We adopt an estimation framework similar to the estimation of human capital spillovers as suggested in Moretti (2004) to test whether there is an additional impact of cultural diversity at the regional level given the plants own composition of its workforce. We extend the econometric strategy to System GMM methods that allow controlling for the potential endogeneity of the diversity measures within the plant and region in the estimation of the plants' production functions.

Overall, we find that the presence of non-native employees in a plant measured as the share of foreigners of a plant's own workforce has no significant impact on the observed productivity of the plant on average. The diversity of the foreign employees with respect to their nationalities, however, increases the total factor productivity in German manufacturing plants, while it has no effect on plants in the service sector. In addition, there is a positive spillover-like effect of the regional diversification of the workforce. The positive impact of the regional workforce is mainly relevant for small plants in the service sector, and for plants in technology- or knowledge-intensive industries. In several robustness checks we try to eliminate alternative explanations for the diversity effect at the regional level, but the finding remains unaffected by the inclusion of further regional characteristics.

We thus conclude that the productivity of German plants in our sample is positively affected by the composition of the plants' own workforce and the composition of the working population of the region the plant is located in. Assessments of the effects of international migration thus should not focus solely on the number of foreign people that are part of an economy. In addition to the cultural enrichment of a society, the diversity found among immigrants has a real positive impact on the host economy that compensates potential costs. The effects seem to be larger in environments in which potential communication barriers are smaller.

This chapter proceeds as follows. The next section presents the empirical strategy. In section 5.3, the databases for the analysis are described, and section 5.4 explains the construction of variables. Section 5.5 shows the results, while the last section concludes the chapter.

5.2 Estimation

To assess the impact of a culturally diverse labor force on the plant's productivity, we estimate plant level production functions augmented with measures for the composition of the workforce at the plant and regional level. The idea behind this modeling approach is that if the diversity among the plants' own workforce has a net positive (negative) productivity effect, plants with workers from various cultural backgrounds should be able to produce more (less) with the same amount of inputs, controlling for other plant and worker characteristics. Similarly, if there are positive (negative) externalities from the composition of the regional workforce, we should observe a higher (lower) level of productivity of plants located in regions with a higher degree of diversity compared to plants in regions with a less diverse population, again controlling for the plants' own labor force composition and other regional characteristics.

The starting point is a log-linearized Cobb-Douglas specification with the plant's value added (VA_{it}) as the dependent variable, and physical capital (K_{it}) and human capital (H_{it}) as standard input factors for plant i in period t:

$$\ln VA_{it} = \alpha \ln K_{it} + \alpha \ln H_{it} + \ln A_{it}. \tag{5.1}$$

We then assume the measures that account for the degree of cultural diversity at the plant and regional level, Div_{it} and $Div_{(-i)rt}$, respectively, to shift the plants' log total factor productivity A_{it} in a linear way:

$$\ln A_{it} = \theta_1 Div_{it} + \theta_2 Div_{(-i)rt} + u_{it}. \tag{5.2}$$

The index $(-i)rt$ indicates that we calculate the variables for region r excluding the i^{th} plant's own contribution to its region's workforce in order to separate the effects of diversity within the plant and at the regional level. The error term u_{it} may include a plant specific unobserved component in addition to the idiosyncratic disturbance term.

We adopt a dynamic framework and include the lagged dependent variable $\ln VA_{i,t-1}$ as an additional regressor. Productivity levels of plants can be expected to display significant persistence over time. Conditioning on the past output level assures that we look at changes in the short run only, while the past evolution of the plant is captured by the lagged output variable. This modeling strategy helps to reduce the reverse causality problem that arises if more productive plants choose to locate in diverse regions. The lagged dependent variable filters out those past factors and helps to identify the short-run effect of diversity on output given past performance. The final regression equation is the combination of the two equations plus the one-period lagged value added and further control variables. We include a vector of additional control variables X_{it} that are known to influence the productivity of a plant, while $Z_{(-i)rt}$ contains further regional characteristics. Finally, industry, region, and year dummies are included (d_j, d_r, and d_t), such that the remaining variation in the value added refers to within industry and within region differences in a specific year.

$$\begin{aligned} \ln VA_{it} &= \rho \ln VA_{i,t-1} + \alpha \ln K_{it} + \alpha \ln H_{it} + \theta_1 Div_{it} + \theta_2 Div_{(-i)rt} \\ &+ \gamma X_{it} + \delta Z_{(-i)rt} + d_j + d_r + d_t + u_{it}. \end{aligned} \tag{5.3}$$

The main challenge in the estimation of the effects of the labor force composition on plants' productivity is the potential bias that arises if unobserved factors drive both the productivity of a plant and its decision to employ a more diverse workforce. If plants with a positive productivity shock tend to hire people from different nations more frequently than less productive competitors, the estimated coefficient of the plant's own diversity in the production function would be upward biased. In contrast to Moretti (2004), who focuses on regional spillover effects alone and considers plant-level workforce characteristics as mere control variables, we are interested in the effects within the plant as well. Therefore, we take into account both the potential endogeneity problem of the plants' own inputs as well as of the correlation of unobserved effects with the regional diversity measures.

We use System GMM methods following Blundell & Bond (1998, 2000) to overcome the problems related to the estimation of such an augmented production function. This estimator uses two equations simultaneously, equation 5.3 in levels and in first differences, where endogenous and predetermined explanatory variables are instrumented with their lagged differences and levels, respectively.[1] We instrument all diversity measures at the plant and regional level in addition to the lagged dependent variable and the plants' physical and human capital.

This estimation strategy has several advantages compared to using panel fixed effects methods. While the time-constant component of unobservable effects could be eliminated using fixed effects estimation methods, productivity shocks that are time-varying and unobservable for the researcher would cause both OLS and fixed effects regression estimates to be biased. Furthermore, including the lagged dependent variable as an explanatory variable in a model with plant fixed effects induces an endogeneity problem by construction, known as dynamic panel bias as described in Nickell (1981). In addition, as the capital measure is not directly observed, but computed from reported investments and industry-level approximations, we expect it to contain some measurement error, which fixed effects methods tend to reinforce (van Biesebroeck, 2007). Finally, we model the presence of migrant workers with their share of the total labor force. Using shares in fixed effects estimations introduces systematical measurement error (compare Gerdes, 2011), that should be less severe in System GMM estimation, where both within- and between-variation contribute to the identification of the estimated parameters.

As this estimation strategy generates more instruments than endogenous regressors, we can perform tests for overidentifying restrictions with the null hypothesis of joint validity of all moment conditions. We report the Hansen J test statistic as it is robust to heteroscedastic standard errors (Roodman, 2009). Unfortunately, there is no reliable test routine for the problem of too many instruments

[1]We do not use difference-GMM as the value added variable appears to be highly persistent making levels poor predictors of the first differences of the time series (Bond, 2002, compare).

available. To be able to judge the quality of the test statistic, we report it together with the number of instruments used. Further, we test for the appropriate autocorrelation structure in the residuals of the first difference equation needed for the lagged variables to be valid instruments (Arellano & Bond, 1991). Finally, we implement Windmeijer's finite-sample correction for two-step covariance matrix estimation, and adjust the standard errors in the regressions for clustering at the region-industry level.

5.3 Data

To assess the impact of cultural diversity on the productivity of plants, we combine the German Establishment History Panel (Betriebshistorik-Panel - BHP), which is generated from the employment statistics by the Federal Employment Agency, with the survey information from the IAB Establishment Panel (EP). Both datasets are provided by the Institute for Employment Research (IAB). The information from the BHP is linked to the EP via a unique common establishment identifier.

The IAB establishment panel is an annual survey of German plants collected in personnel interviews (for more information, see Kölling, 2000). Drawn from the population of all German plants with at least one employee subject to social security, the sample is stratified across plant size and industries. Due to the way of data collection, the unit of observation is the individual establishment. An establishment refers to the local unit of production as opposed to the concept of a firm that could comprise several plants. Following Harris et al. (2005), the plant as the lowest production unit is suited best for the estimation of productivity for several reasons. Firms often operate plants in various industries, which would make it difficult to control for industry-specific influences with industry dummy variables. More importantly, the impact of regional characteristics would be diluted by firms with plants in more than one region. Finally, the probability for actual interaction between workers of different nationalities is higher within plants compared to a geographically spread firm. The establishment panel provides a wide range of self-reported plant variables, ranging from data on sales, investments, and employment to exporting behavior and organizational characteristics. We take all necessary plant-level information from the EP except for the details on the employed workforce, as much more detailed information is provided in the administrative data of the BHP (Hethey & Schmieder, 2010).

The second data source, the BHP, is a 100% sample of all German establishments employing at least one person subject to social security (thus excluding civil servants and self-employed). Based on process data from the German Federal Employment Agency, the BHP is highly reliable, and it comprises a comparably rich set of variables. The data contains not only information on a plant's location (NUTS 3 regions), the industry in which the establishment operates (three-digit NACE codes), but also a set of variables that describe the plants' workforce: gender, occupation and - most importantly for our analysis- the nationality of the plants' employees. The classification of foreign nationalities is very detailed with around 180 different categories. The data is aggregated at the plant level to calculate the diversity measures and further workforce characteristics. As the coverage is universal, regionally aggregated variables generated from this data describe the environment for each single plant most reliably, in particular with respect to the variables that consider the nationality of the employees. The combination of the data with the establishment panel allows us to control for regional characteristics based on the BHP in the analysis of the establishments' performance using the EP. We focus on the period from 1999 to 2008, as from 1999 onwards the survey's definition of the plant population is consistent over time.[2]

The sample consists of manufacturing and services firms for which all necessary information is available for at least three consecutive years to ensure the availability of appropriate lagged instruments. We only consider establishments that are profit oriented; non-profit organizations, the public and the financial sectors are excluded.[3] We drop plants that switch between regions or change their reported industry, and delete plants that insource other plants or units that are bought by other firms to ensure consistency over time.

5.4 Variable definitions

In this section, we describe the construction of variables that we need for the estimation of equation 5.3. Table 5.1 provides a list of all variables and more information on the data used for each measure.

[2]From 1999 on, the data includes establishments with only minor employed persons.

[3]The following three digits NACE codes are excluded: 11, 12, 13, 14, 20, 651, 652, 751, 752, 803, 950.

5.4.1 Production function variables

The dependent variable is an establishment's value added calculated from the plants reported sales minus intermediate inputs. To measure the plants' use of labor inputs, we calculate the average daily employment in full-time equivalents.[4] As the value of sales relates to an annual value, using full-time equivalents approximates the necessary labor input for the yearly production output far better than the alternative headcount as per period end, a measure that varies considerably over the year due to seasonal effects. Using average daily employment also helps to control for part-time workers.

To account for differences in the plants' human capital, we differentiate between highly skilled and less skilled employees. Skilled labor input is often approximated by employees holding a university degree. While this information is available in our data, we prefer to use a more comprehensive measure that takes into account assigned tasks of different occupations. For a practical reason, the traditional skill measure is frequently not reported and we would lose more than half of the final observations that do contain information on occupations. Further, high skilled people do not necessarily work in occupations that typically ask for a university degree and there are also many employees without higher education that work in occupations that typically do ask for a degree (Brunow & Hirte, 2009). This problem can be expected to be even more severe comparing native and foreign employees, as the different degrees might be less comparable across nations. Peri & Sparber (2009) and D'Amuri & Peri (2010) also show that within education categories, natives and non-natives specialize in different tasks for which they have a comparative advantage. We take the data on occupations from the 1998/99 German Qualification and Career Survey conducted by the Federal Institute for Vocational Education and Training (BIBB) and the Institute for Employment (IAB). Based on the share of analytical work and the share of non-routine tasks relative to total working time in addition to the average share of people holding a university degree that characterize each occupation, we classify occupations into a high skilled and

[4] The BHP reports the number of employees in three categories: working full-time, large, and small part-time. A full-time equivalent is then estimated using the weights 1, 0.6, and 0.3 for the different categories, respectively. The weighting is necessary, because no information on hours worked is provided.

less skilled group using hierarchical cluster analysis.[5,6]

As many comparable establishment-level datasets, the EP does not contain a direct measure of the capital stock. There is information available on the plants' total investments, the share of net investments, and dummies for four categories of investment types (real estate, IT, production machinery, and transport equipment). We apply the modified perpetual inventory method developed explicitly for this dataset by Müller (2008). Due to the rather short panel dimension, a starting value for the capital stock is computed based on a proportionality assumption using industry specific information on average economic lives of different types of equipment and average investments in the first three observed years. Based on this starting value, a perpetual inventory approach is used to generate the capital stock for each year.

5.4.2 Diversity measures

The main variables of interest are the diversity of the plants' and regions' workforce with respect to foreign nationalities. To measure the effect of a culturally diverse workforce, we use two variables. The share of employed foreigners in the total workforce s_{it}^{for} captures the size of the group of foreign employees. The diversification of the foreign workforce is measured with a Herfindahl-Hirschman type index that reflects the distribution of nationalities among the foreign employees:

$$div_{it}^{for} = 1 - \sum_{m=1}^{M_{it}} s_{m_{it}}^2. \tag{5.4}$$

$s_{m_{it}}$ is the share of workers of nation m in the total number of foreign workers employed at plant i at time t, $m = 1, \ldots, M_{it}$, and M_{it} is the absolute number of nations within the respective plant. Note that div_{it}^{for} equals zero for plants that employ persons from one single foreign nation, as well as for plants that employ natives only. The index rises with the number of different nationalities employed at a plant. For a given M_{it}, the measure is higher the more uniformly distributed

[5]The proportion of employees with a university degree is taken from the BHP data base.

[6]Given the identical continuous scale of the three variables we choose the Euclidean distance to measure similarities between occupations. The results used are based on a complete linkage, where the furthest distance of objects within two clusters is used to merge objects and clusters. Other methods lead to qualitatively similar clusters.

the shares $s_{m_{it}}$ are, and it reaches its maximum if the same number of employees from each nation is employed in a plant at $div_{it}^{for} = 1 - 1/M_{it}$.[7]

Two reasons let us choose this operationalization of cultural diversity with two separate variables. While the main interest lies on the diversity index, the share of foreign employees is included to capture the level effect of the presence of foreign employees. We want to stress that the composition of the group of migrants is a second, separate dimension of migration that is often neglected in studies on the effects of immigration. There is a second, more technical aspect. Alternatively, we could construct a diversity measure including the share of natives. However, the resulting index over all nations turns out to be completely dominated by the share of German labor input leaving almost no variation across time, regions, and plants for identification. It has to be kept in mind that the estimated effects of diversity can only be interpreted conditional on the share of foreign employees.

As a proxy for the cultural background of an employee, we use the employees' nationality as in Südekum et al. (2012). One potential drawback of the diversity measure is that only the actual, recorded nationality is reported in the IAB data. Neither the country of birth, nor the naturalization of migrants is documented in official statistics in Germany. When immigrants change their nationality, our measure would underestimate the degree of diversity. The same would be true for second-generation immigrants that have German citizenship but define themselves in terms of their parents' culture. As information on the time since migration or language skills is also lacking, we could also overestimate diversity, as the cultural differences might diminish and language skills improve with the time a foreign worker is living in Germany. While one should keep in mind these limitations, it has to be clear that this type of information would only be available in survey data. The construction of variables at the regional level, however, hinges on the availability of information on the universe of the workforce only available in administrative data.

[7]There are several ways discussed in the literature to control for diversity. We use the traditional Herfindahl-Hirschman index. Other measures are discussed by Combes et al. (2004) and Ottoviano & Peri (2005) and lead to similar results.

5.4.3 Control variables

With regard to the control variables included in the regression analysis, we consider additional measures that characterize the plants' workforce such as the share of female employees and the share of part-time work.[8]

The next set of variables refers to plant-level characteristics that are known to influence productivity significantly. Exporting plants are relatively more productive than their domestic competitors as they have to incur entry costs in the foreign market (Melitz, 2003; Wagner, 2007). Similarly, foreign-owned firms typically display a higher efficiency level (Conyon et al., 2002b). We include an age dummy for young firms and control both for the legal form and for plants that are part of a larger corporate group. We further use a question about the current state of the technology and machinery (state-of-art versus out of date) to control for qualitative differences of the plants' technical equipment.

To capture the impact of the regional workforce on the plants' productivity, we calculate further control variables at the NUTS 3 level. As described above, we always exclude the individual plant under consideration in the calculation to avoid endogeneity and multicollinearity problems. We use region size in terms of total employment to account for urbanization effects.[9] Large areas typically offer better job opportunities making immigration more likely. An omission of such a measure would overestimate regional diversity effects. Additionally, we control for the stock of human capital in the plant's location.[10] Further regional control variables such as industrial diversity are considered in robustness checks.

5.5 Results

5.5.1 Descriptive statistics

Before we present the regression results, we discuss the characteristics of the estimation sample displayed in table 5.2. Overall, the average share of foreign em-

[8]We do already control for part-time work in the full-time equivalents to define the volume of labor, but there might be a loss in overall productivity when the average proportion of part-time work increases.

[9]We also experimented with the regions density and other regional characteristics without changing the main results.

[10]The construction of regional variables is only reliable from the universe of administrative data. We are not able to construct regional capital stock variable from the survey data as a further regional control variable.

ployees working in plants included in the estimation sample is 3.6%. The share rises to 10.8% for plants with a positive share of foreigners.[11] The proportion of foreigners across all plants is rather constant over the sample period and the number is almost the same for manufacturing and service plants. The share of foreign workers is higher among less skilled workers in both sectors, but service plants employ relatively more high skilled migrants compared to manufacturing plants. Further, larger plants and those that are located in agglomerated regions employ a higher proportion of foreign workers than their smaller competitors and plants in more rural areas, respectively. Regional differences are pronounced with a share of foreigners of 6.7% in western plants, compared to only 0.5% in plants located in the former Eastern German regions, a fact that is driven by the lower general presence of migrants in Eastern Germany.

The second dimension of cultural diversity is the distribution of different nationalities among the foreign workers. The diversity index is on average 0.16 for all plants, and 0.41 for plants with at least one foreign employee. Diversity among less skilled migrants is higher than among high skilled workers, and manufacturing plants employ a more diverse mix of foreign workers. Again, the numbers are much higher on average for western plants than for their East German counterparts (0.45 versus 0.18), and also for larger plants and plants located in large, agglomerated regions.

Turning to the region level, the average share of foreigners in the regional workforce is 5.6% and the diversity index has a mean of 0.86. The proportion of foreign workers among the less skilled workforce is 8.1% compared to 2.7% among the high skilled employees. As indicated earlier, there is a large difference between the Western and Eastern German states, where we observe both a higher share and more diverse foreign workers in the Western states (the share is 7.0% versus 0.7%, respectively). The regions with the highest proportion of foreigners are the metropolitan areas around Munich, Stuttgart and Frankfurt, as well as in the Rhine-Ruhr area. The diversity index varies considerably and takes on values between 0.30 and 0.97, where typical university towns, such as in Trier or Jena, have the most diverse workforce. The traditional guest worker regions, in contrast, display the lowest diversity values due to the strong presence of employees from

[11] We also do observe a small number of plants that have a share of foreigners equal to one, which are very small plants mainly in restaurants and retail sale business.

former guest worker countries, such as Turkey or Greece, that dominate the distribution of nationalities. The diversity index at the regional level separated by skill group takes slightly higher values for high skilled foreign employees.

Economically strong and agglomerated regions should attract more migrants than smaller regions as they provide more job opportunities. The proportion of foreign workers is thus expected to be higher in larger and richer regions. The correlation between region size and diversity is less clear ex ante. Again, prosperous regions attract migrants from many countries increasing the mix of nationalities. But the literature also describes a network effect, according to which new migrants tend to settle in regions where other members of their home country already live Bartel (1989). If, historically, a certain migrant group is more present in an agglomeration, such as from the Southern European countries or Turkey in the Rhein-Ruhr area, this region further attracts immigrants from the same country of origin, which would imply a decrease in diversity. The two panels of figure 1 show the correlation of the regions' share of foreign employees and the diversity index with the log region size, respectively. While the proportion of foreigners in the population clearly rises with the total size of a region, there is no significant relation to the regions' diversity index.

The focus of the following analysis is the separation of the effect of diversity at the region and plant level. Table 5.3 displays the matrix of pairwise correlation coefficients for the respective variables. The correlation coefficient between the plant and region share of foreign workers is positive, that is, plants in regions with more migrants tend to employ more foreign workers not controlling for any other characteristics. But it is interesting to note that the correlation between the diversity index measured at the plant and region level is negative, which indicates the importance to separate the effects of a diverse workforce within a plant from spillover effects stemming from the regional composition of the workforce.

Further, we measure diversity with two separate variables, the ratio of foreign labor input to total employment and the diversification among the foreign workforce. The correlation between the share of foreigners and the diversity index is positive at the plant level, but negative at the regional level. Plants that employ many non-natives also tend to have a more diverse workforce. Regions where many foreign employees live, in contrast, are not necessarily diverse with respect to the nationalities of the migrants. In fact, the two measures capture distinct dimensions of migration.

5.5.2 Main results

We now discuss the estimation results. Table 5.4 presents the results for the production function estimation using different estimation strategies. The estimation is carried out separately by the two broad sectors manufacturing and services. Focusing on the coefficient of the lagged dependent variable, OLS results in the first columns are highest, fixed effects estimations give the lowest values displayed in the second columns, while the coefficient obtained in the System GMM estimation depicted in the last column is in the middle of the two estimates. This is in line with theoretical considerations, where OLS estimates of the coefficient of the lagged dependent variable in the presence of plant fixed effects are upward biased, and fixed effect estimation leads to downward biased estimates (Roodman, 2009). The Hansen J test does not reject the null of joint validity of all instruments. The test on autocorrelation in the residuals of the equation in first differences cannot reject the null of no autocorrelation of second order, which means that there is no autocorrelation of first order in the level equation aside from the plant fixed effect. As our System GMM estimates lie in the predicted range and the test statistics support the dynamic specification and appropriate instrumentation of the endogenous variables, we are confident that we have a robust specification of the production function.[12]

Briefly looking at the standard control variables, their coefficients turn out to have the expected signs as well: plants with newer technology produce more efficiently, single plants are less productive than plants that are part of a larger group, and foreign ownership as well as exporting activity are both associated with higher productivity at least in the manufacturing sample. The share of females and part-time work are measures that characterize the plants' human capital in more detail. The negative coefficient of the proportion of females working in a plant can be explained with an on average reduced number of working hours of female employees even after controlling for the broader categories part-time and full-time employment. In the service sector, plants with a higher share of part-time work might be

[12] A minor issue is the insignificant coefficient estimate of the capital measure in the manufacturing sample. The capital measure is an approximation calculated from investment figures and a constructed starting value. The instrumentation with lags in the System GMM estimation takes into account potential measurement error that seems to be present in the constructed capital measure. Nevertheless it is important to control for capital as an input factor to get reliable estimates for the remaining measures of the plants' inputs.

able to respond more flexibly to short-term demand variations.

Turning to the regional control variables, the log size of the plants' region in terms of the total number of employees captures agglomeration effects. We also add a regional measure for human capital in the spirit of Moretti (2004) as the regional share of skilled workers could confound the effect of diversity at the regional level if diversity varies systematically with the skill share. In the manufacturing sample, plants located in larger regions in terms of the workforce appear to be more productive, a result in line with Andersson & Lööf (2011) who find the same effect for Swedish manufacturing plants. However, the region size is no longer significant with the introduction of the additional regional control variables. In the service sector, both the size of the region and the regional share of human capital are statistically insignificant in the estimation of the plants' productivity. As these results remain basically unaffected from the sequent introduction of the variables of interest, we suppress them in the following tables for the sake of brevity.[13]

We now look at the main variables of interest that measure the cultural diversity among the plants' workforce and in the region of the plant, namely the share of foreign employees and the diversity index among those foreign workers. At the plant level, the coefficient of the share of foreigners in the manufacturing plants' own workforce is negative, but the coefficient is insignificant in the estimation. However, we see a statistically significant, positive coefficient of diversity among the foreign employees on manufacturing plants' observed total factor productivity. To get a feeling for the economic significance of this effect in the semi-log specification, we calculate the productivity change implied by a one standard deviation increase in the plants' diversity index. The resulting increase of 9.7% (=(exp(0.310)*0.300)-1*100%) seems to be reasonable as it lies between the productivity advantage of having the newest technology (6.8%) and having a foreign owner (15.7%). In the service sector, the diversity index appears to have an insignificant impact on the plants' productivity.

Turning to the regional level, the regional share of foreigners is also not significant in the estimation. The regions' diversity index has a significant and large coefficient, however. If the regional diversity index rose by one standard deviation in the manufacturing sample holding constant the share of foreign workers, the observed productivity of an average plant would thus rise by around 11.4%

[13]The full sets of results are available upon request.

(=(exp(1.617*0.067)-1) *100%) given its own composition of the workforce. At the regional level, the presence of foreigners, the proportion of skilled employees, and the size of the region is positively correlated so that it is hard to separate the effects on plant productivity from each other. It has to be clear, though, that the effect of a diverse population can only be interpreted conditional on the share of foreigners present at the plant or region.

Summing up, we find that cultural diversity matters for plant performance. The size of the group of foreign workers, in contrast, does not have an effect on plant productivity. We find two channels for the impact of diversity on productivity. The composition of the plant's own workforce shows up for manufacturing plant, but plants from both sectors benefit from their location in a culturally diverse region, and this effect is economically at least as important as the effect within the plant.

One possible explanation for the results could be that communication difficulties are more problematic in the service sector that is characterized by a closer and more direct customer interaction than in manufacturing. In manufacturing firms, the positive effect of complementarities of skills and knowledge of the diverse workforce seems to dominate. In addition, manufacturing firms might have different innovation behavior than service firms. There is evidence that service firms are more dependent on inter-firm co-operations, while manufacturing firms are often seen as "true innovators" that innovate within their own firm boundaries (Tether, 2005). Niebuhr (2010) shows how cultural diversity is related to innovation at the regional level in Germany via the combination of new ideas and problem solving abilities. Taken together, these pieces of evidence help to understand the differences across sectors found in our results. Another way to support this line of reasoning is to look at high-tech and knowledge-intensive industries, for which the effect of diversity should be particularly pronounced. Indeed, the first two columns in table 5.5 show that the effect at the regional level stems from the part of the sample that belongs to these technology-intensive industries.[14]

[14] A finer sector definition according to Eurostat in high-tech and low-tech manufacturing and knowledge intensive and other services did not give any significant results supposedly because of the reduced sizes of the subsamples.

5.5.3 Effect heterogeneity

If we really measure a spillover-like effect of diversity, the effect of the regional diversity on single plants can be expected to be more pronounced than for plants that are part of a group, as for the relation between regional characteristics and plant outcome should be more direct for single plants. In fact, the results are mainly driven by the subsamples of single plants (compare table 5.6). As the sample sizes are reduced by this additional sample split, the regressions for plants that are part of a larger corporate group should be interpreted with care, however, as the test statistics point to problems with the instrumentation of the endogenous variables (p-values of the Hansen J test is exactly 1).

Another explanation that goes into a similar direction can be derived from the separate estimations for large and small plants. The positive coefficient within the plant pops up within larger manufacturing plants that benefit from their own diverse workforce, but there is no spillover effect from the regional workforce. For smaller service plants, in contrast, the results suggest the opposite: they are stimulated by a diverse environment, and the coefficient is much larger compared to the pooled sample results. Note that there is a slightly significant negative effect of the presence of foreign workers in small service plants. Again, one reason could be that the communication costs in customer-oriented service plants without the organizational structure of larger plants are most severe. As service plants in the sample are on average smaller than manufacturing plants, this result partly explains the sectoral differences (table 5.7).

Another channel for the positive impact of diversity on plant productivity could be via the plants' exporting behavior. Plants with employees from various nations might find it easier to enter foreign markets and to build up distribution networks in various countries. Foreign employees possess special knowledge about the export destination country, they know not only the language, but also tastes, habits, and laws, information that might be crucial to be a successful exporting plant. Therefore, we re-estimate the same equation separately for exporters and non-exporters in table 5.8. Interestingly, the share of foreign workers now turns out to be negatively related to non-exporting plants' productivity. The benefits of foreign employees thus seem to be larger for exporters, while the costs associated with workers from other nations appear to be more dominant in the rest of the plants. A different explanation might be that exporters might have a common working language within the plant anyway due to their international engagement, making communication between native and non-native employees more efficient.

Further, the impact of the regional composition of the workforce shows up only for the non-exporter sample. Exporters seem to be less dependent on their region's characteristics as they operate on more than one market. In contrast to this result, the impact of regional diversity is the same for foreign-owned and domestic plants. The effect on the foreign-owned plants is in fact higher. Again, the test statistics in this estimation are less satisfactory (table 5.8).

Finally, we try to assess regional differences in our findings. Table 5.9 shows the results of separate estimations for different types of regions. The effect of regional diversity reveals a surprising pattern: the coefficient is very small for agglomerated regions, and larger and significant only for less urbanized regions. Further, we separate the sample into plants located in larger and smaller regions with respect to the region size. Again, the effect at the regional level seems to be driven mainly by plants in smaller regions, while there is no spillover effect from a diverse workforce in larger regions.[15] One explanation for this somewhat surprising finding could be that in larger, agglomerated regions, there is already quite a diverse population with regard to their background, experiences, and skills irrespective of whether migrants are present or not. In less densely populated regions, on the other hand, diverse migrants really add new knowledge and abilities to the available pool resulting in an increase of the regions' and plants' productivity. Another way to look at the results is that smaller plants are more frequently located in rural areas and thus the differences in the effects across regions is the consequence of the different composition of plants.

5.5.4 Robustness checks

One might wonder whether the regional diversity effect captures other urbanization effects than effects related to cultural diversity. Migrants are not distributed evenly or randomly across the country, but they self-elect into particular regions. It has to be clear, however, that we do already control for regional size that should absorb all effects related to the size of the region in addition to region and industry fixed effects that take into account time-invariant regional differences. Additionally, the lagged value of plant's value added ensures that only short-term effects

[15] The following variations did not result in significant coefficient estimates: A separate estimation for three regional types (agglomerations, urban and rural areas), the introduction of interaction terms of the region size or region density with the diversity measures.

are estimated while general level effects or reverse causality issues are controlled for. Finally, the remaining potential endogeneity of the diversity measures is taken into account as we instrument both the regional and plant diversity variables. Still, GMM results could suffer from weak and too many instruments. Therefore, we try to exclude alternative explanations for the effects found using more control variables and alternative estimation strategies. As additional region characteristics we include regional density, the number of plants in the region, the number of plants in the industry and region, and the industrial diversity of the plants across industries. All of these variations do not change the estimated effects of cultural diversity of the regional workforce (table 5.10).

A major problem could be that the diversity measure partly captures industry-specific productivity shocks that are not absorbed by industry fixed effects. If diversity increases as migrants are attracted to certain industries and regions that experience a positive productivity shock, our results could be spurious. To check this possibility, we follow Moretti (2004) and calculate the regional diversity measure excluding not only the plants' own contribution in the calculation of the regional variables, but we subtract the contribution of the plants' own industry in the regional diversity measures. The results are basically the same, but the level of significance decreases. While part of the effect might be industry-specific, this result gives even more confidence in the chosen IV framework, as potential unobserved industry productivity shocks seem not do drive our results (compare table 5.11).[16]

Diversity could matter more within skill groups as the interaction between the members of the groups is more direct. If the positive effect of diversity is due to increased problem solving abilities, the effect can be expected to show up for the high skilled group that is defined by occupations with a high share of analytical, non-routine tasks. In addition, better educated people might have less communication problems. Therefore, we calculate the results for the diversity measures separated by skill. Table 5.12 reveals that no coefficient is now significantly different from zero. As the estimation is very data demanding already by including many control variables and various fixed effects, it is not possible to identify significant separate effects. We thus do not further pursue the estimation of separate effects by skill groups.

[16]One could also try to assess the effect of diversity within the plants own industry excluding the plants contribution. However, at this level of regional disaggregation, there are often too few plants per industry that the calculation of an average remains meaningful.

One concern might be that not only the skill structure might be different for plants with more foreign workers, but that the observed effect of diversity might stem from differences in the mix of occupations in the plants. Peri & Sparber (2009) and D'Amuri & Peri (2010) suggest that migrants tend to chose occupations where they have a competitive advantage over natives, and migrant concentration varies between industries and firms (Andersson et al., 2010). The occupational diversity index among foreigners is also much smaller in our sample than the index for native workers. We thus include an occupational diversity index and in another variation separate indices of occupational diversity among native and non-native employees in the estimation equation. The results are insignificant for the new variables and the main results are mainly unchanged. The sorting of migrants into specific occupations and resulting productivity gains do not drive primarily our findings (table 5.13).

When sales are used as the dependent variable instead of value added (first columns in table 5.14) or with intermediates as an additional input factor and sales as the dependent variable (last columns in table 5.14), the direction of the effects remains largely the same. In this specification, sales seem to be more correlated over time, the lagged dependent variable captures more of the variation leaving the other input coefficients with lower coefficients, and also the size of the regional effect is smaller. Robustness checks using information on the employees' high school degree generate similar results, but the coefficients lose their significance. This is mainly due to the loss of more than half of the observations as this variable is frequently not reported in the data in contrast to the occupational information (table 5.15).

5.6 Conclusion

This chapter analyzes the impact of a culturally diverse workforce within plants and regions on plant productivity for a comprehensive sample of German establishments. Using System-GMM methods to estimate plant-level production functions augmented with regional information we control for the potential endogeneity of the diversity measures within the plant and region.

We find that the presence of non-native employees in a plant has no significant impact on the observed productivity of the plant on average. The diversity of the foreign employees with respect to their nationalities, however, increases the total factor productivity in German manufacturing plants, while it has no effect on plants in the service sector.

In addition, there is a positive spillover effect stemming from the regional diversification of the workforce. The positive impact of the regional workforce is mainly driven by small plants in the service sector, and also shows up for plants in technology- or knowledge-intensive industries. The number of foreign employees in a region does not have a significant impact on plant productivity, however. The estimated effects survive a series of robustness checks in which we try to eliminate alternative explanations for the diversity effect at the regional level.

The policy debate and also the larger part of the migration literature focuses on the absolute number of migrants, while the cultural diversity among migrants as the second dimension of international migration is often not taken into account. The composition of the plants' own workforce and the composition of the working population of the region the plant is located in have a real positive effect on productivity of German plants in our sample.

We extend the research that finds positive diversity effects on regional productivity as we provide evidence on two different channels through which the observed effects arise. Part of the effect has its origin within the plants, but at least as important are knowledge externalities at the region level that improve the plants' efficiency.

The costs that are usually associated with a diverse workforce seem to be outweighed by the synergies that are created when different and new skills and abilities are combined. Interestingly, this productivity effect does not arise clearly from interactions within skill groups. Whether cultural diversity within a plant can enfold its positive impact rather seems to depend on the business environment in the plant. In large, exporting, manufacturing plants, English is usually the business *lingua franca*, which reduces potential disadvantages of migrants and the positive effect of diversity is observed. For other plants to be able to benefit the most from international diversity, it might be helpful to eliminate existing language barriers to reduce communication costs.

5.7 Tables

Table 5.1
Variable definitions.

Variables		Source	Details
Production function variables			
VA_{it}	Value added	EP	Sales minus intermediates, in Euro
K_{it}	Physical capital	EP	Constructed from investments following Müller (2008), in Euro
H_{it}	Human capital	BHP	Average daily employment in full-time equivalents
	High skilled labor input	BHP	Skilled labor according to the employee's occupation
	Less skilled input	BHP	Less skilled labor according to the employee's occupation
Diversity variables			
S_{it}^{for}	Share of foreigners	BHP	Share of labor input of non-native employees
	Share of high skilled foreigners	BHP	Share of high skilled labor input of non-native employees
	Share of less skilled foreigners	BHP	Share of less skilled labor input of non-native employees
Div_{it}^{for}	Diversity among foreigners	BHP	HHI type diversity index $div_{it}^{for} = 1 - \sum_{m=1}^{M_{it}} s_{m_{it}}^2$ with M_{it} number of different foreign nations within the plant
	Diversity among high skilled foreigners	BHP	Calculated across all foreign nations of high skilled employees
	Diversity among less skilled foreigners	BHP	Calculated across all foreign nations of less skilled employees
$S_{(-i)rt}^{for}$	Regional share of foreigners	BHP	Calculated excluding the plants' own workforce
$Div_{(-i)rt}^{for}$	Regional diversity among foreigners	BHP	Calculated excluding the plants' own workforce
Control variables			
	Share of females	BHP	Share of labor input of female employees
	Share of part time	BHP	Share of labor input of employees working part-time
	Exporter dummy	EP	Positive sales abroad = 1
	New technology dummy	EP	State-of-art equipment = 1
	Foreign owned dummy	EP	Establishment majority owner is foreign = 1
	Single plant dummy	EP	Establishment is single plant = 1
	GmbH dummy	EP	Establishment is a private limited company "GmbH" = 1
	AG dummy	EP	Establishment is a public limited company "AG" = 1
	Regional workforce	BHP	Sum of regional labor calculated excluding plants' own workforce
	Regional share of skilled labor	BHP	Calculated excluding the plants' own workforce

Table 5.2
Descriptive statistics of the estimation sample.

	Manufacturing		Services	
	Sample mean	Standard deviation	Sample mean	Standard deviation
Plant specific variables				
Share foreigners	0.035	0.076	0.036	0.097
Diversity among foreigners	0.181	0.300	0.135	0.274
Share of high skilled foreigners	0.012	0.042	0.021	0.082
Share of less skilled foreigners	0.046	0.099	0.049	0.140
Diversity among high skilled foreigners	0.086	0.226	0.064	0.198
Diversity among less skilled foreigners	0.154	0.276	0.093	0.234
Log value added	14.551	1.901	14.051	1.687
Log labor	9.598	1.568	8.950	1.440
Log capital	14.337	2.250	14.087	2.481
Share of skilled labor	0.318	0.193	0.512	0.301
Share of female labor	0.273	0.220	0.392	0.271
Share of part-time labor	0.051	0.100	0.129	0.213
New Technology dummy	0.671	0.470	0.738	0.440
Single plant dummy	0.800	0.400	0.742	0.438
Foreign owner dummy	0.092	0.289	0.038	0.191
Exporter dummy	0.542	0.498	0.177	0.382
GmbH dummy	0.752	0.432	0.595	0.491
AG dummy	0.028	0.165	0.039	0.192
Regional specific variables (excluding the plant's own contribution)				
Share foreigners	0.033	0.039	0.045	0.041
Diversity among foreigners	0.894	0.067	0.883	0.074
Share of high skilled foreigners	0.018	0.018	0.025	0.021
Share of less skilled foreigners	0.046	0.060	0.066	0.067
Diversity among high skilled foreigners	0.906	0.074	0.903	0.083
Diversity among less skilled foreigners	0.877	0.070	0.864	0.076
Share of skilled labor	0.093	0.039	0.101	0.042

Table 5.3
Correlation coefficients of the main explanatory variables.

		Plant level		Region level (excluding the plant's own contribution)	
		Share of foreigners	Diversity among foreigners	Share of foreigners	Diversity among foreigners
Manufacturing					
Plant level	Share of foreigners	1.000			
	Diversity among foreigners	0.558	1.000		
Region level (excluding the plant's own contribution)	Share of foreigners	0.627	0.581	1.000	
	Diversity among foreigners	-0.324	-0.301	-0.530	1.000
Services					
Plant level	Share of foreigners	1.000			
	Diversity among foreigners	0.408	1.000		
Region level (excluding the plant's own contribution)	Share of foreigners	0.386	0.410	1.000	
	Diversity among foreigners	-0.199	-0.055	-0.448	1.000

Figure 5.1
Region diversity and log region size.

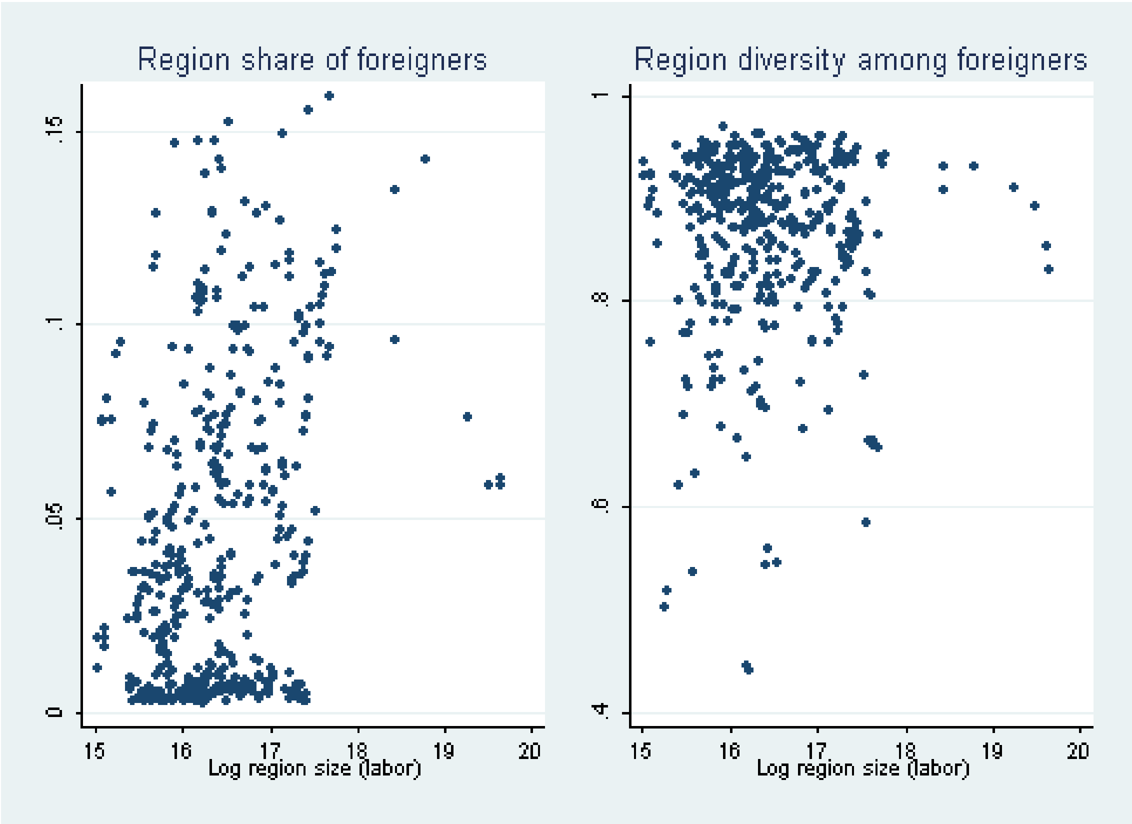

Table 5.4

Estimates of the augmented plant-level production function using different estimation strategies.

	Manufacturing						Services					
	OLS		Fixed effects		System GMM		OLS		Fixed effects		System GMM	
Plant specific variables												
Share of foreigners	-0.204**	(0.090)	0.051	(0.328)	-0.041	(0.379)	0.147	(0.093)	0.354	(0.467)	-0.887	(0.573)
Diversity foreigners	0.046*	(0.027)	0.109*	(0.058)	0.310**	(0.142)	0.090**	(0.042)	0.167	(0.121)	0.033	(0.280)
Lagged log value added	0.706***	(0.013)	0.155***	(0.025)	0.369***	(0.044)	0.738***	(0.017)	0.096***	(0.037)	0.377***	(0.043)
Log less skilled labor	0.123***	(0.010)	0.221***	(0.038)	0.288***	(0.053)	0.057***	(0.008)	0.095***	(0.031)	0.137***	(0.045)
Log high skilled labor	0.112***	(0.009)	0.107***	(0.029)	0.206***	(0.052)	0.107***	(0.011)	0.094**	(0.039)	0.245***	(0.060)
Log capital	0.046***	(0.005)	0.096***	(0.028)	0.016	(0.038)	0.052***	(0.006)	0.032	(0.064)	0.067*	(0.037)
Share female	-0.173***	(0.034)	0.045	(0.206)	-0.432***	(0.074)	-0.097**	(0.043)	-0.292	(0.230)	-0.197*	(0.117)
Share part-time	0.058	(0.054)	0.033	(0.191)	0.104	(0.116)	0.126***	(0.042)	-0.073	(0.117)	0.281***	(0.098)
New Technology	0.022*	(0.012)	0.006	(0.017)	0.051**	(0.020)	0.057***	(0.020)	0.027	(0.033)	0.098***	(0.033)
Single plant	-0.062***	(0.016)	-0.013	(0.034)	-0.160***	(0.032)	-0.053**	(0.022)	-0.119**	(0.055)	-0.186***	(0.066)
Foreign owner	0.010	(0.021)	0.066	(0.049)	0.117***	(0.045)	0.019	(0.036)	-0.402**	(0.198)	0.047	(0.076)
Exporter	0.063***	(0.015)	0.018	(0.026)	0.186***	(0.041)	0.048**	(0.022)	0.032	(0.053)	0.118***	(0.040)
GmbH	0.040**	(0.015)	0.050	(0.045)	0.158***	(0.047)	0.051**	(0.020)	0.062	(0.070)	0.156**	(0.062)
AG	-0.002	(0.035)	0.164	(0.131)	0.164**	(0.083)	0.124**	(0.052)	0.011	(0.155)	0.363**	(0.151)
Regional specific variables (excluding the plant's own contribution)												
Share of foreigners	-0.370	(0.414)	1.932	(3.847)	0.267	(3.000)	0.980	(0.698)	-5.983	(5.818)	4.248	(4.904)
Diversity foreigners	0.193*	(0.101)	0.103	(0.383)	1.617**	(0.705)	0.613***	(0.168)	0.787	(0.680)	1.817**	(0.829)
Region size	0.035**	(0.015)	0.429	(0.365)	0.072	(0.048)	0.014	(0.022)	-0.048	(0.543)	0.027	(0.074)
Region share skilled	0.227	(0.210)	-2.926	(2.173)	-0.387	(0.571)	-0.154	(0.275)	-5.140*	(2.773)	-0.177	(0.683)
Constant	0.843***	(0.257)	0.808	(6.071)	2.049**	(0.843)	0.850**	(0.417)	11.850	(9.261)	3.060**	(1.401)
Year dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Industry, region dummies	Yes		No		Yes		Yes		No		Yes	
Statistics												
Number of observations	7,241		7,241		7,241		4,102		4,102		4,102	
Number of instruments					580						573	
Hansen J p-value					0.559						0.395	
AR(1) p-value					0.000						0.000	
AR(2) p-value					0.125						0.764	

Robust standard errors adjusted for clustering. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Firm controls: Lagged log value added, log less skilled labor, log high skilled labor, log capital stock, share women, share part-time workers, new technology dummy, single plant dummy, foreign owner dummy, exporter dummy, GmbH and AG dummy. Region controls: Log size of workforce, share of high skilled. Industry, region, and year dummy variable sets included. For variables definitions see table 1. Manufacturing Industries: NACE codes 15-37. Service Sector: NACE codes 50-55, 60-67, 70-74, 85, 92-93. High-tech manufacturing: NACE codes 24, 29, 30-35, excluding 351. Low-tech manufacturing: NACE codes 15-23, 25-28, 351, 36, 37. Knowledge-intensive services: NACE codes 61, 62, 64, 66, 67, 70-74, 80, 85, 92. Other services: NACE codes 50-52, 55, 60, 63, 90, 91, 93. Source: Eurostat.

Table 5.5
System GMM estimates of the augmented production function –
Low- and high-tech industries.

	Low-tech manufacturing and other service plants		High-tech manufacturing and knowledge-intensive plants	
Plant specific variables				
Share of foreigners	0.074	(0.458)	-0.192	(0.452)
Diversity among foreigners	0.081	(0.191)	0.090	(0.169)
Regional specific variables (excluding the plant's own contribution)				
Share of foreigners	-1.391	(3.831)	4.860	(3.923)
Diversity among foreigners	0.531	(0.746)	2.858***	(0.934)
Statistics				
Number of observations	7,110		4,233	
Number of instruments	580		575	
Hansen J p-value	0.419		0.994	
AR(1) p-value	0.000		0.000	
AR(2) p-value	0.886		0.130	

All comments and control variables as in table 5.4.

Table 5.6
System GMM estimates of the augmented production function –
Single plants.

	Manufacturing				Service			
	Single plants		Part of groups		Single plants		Part of groups	
Plant specific variables								
Share of foreigners	-0.158	(0.388)	-0.936	(0.839)	-0.685	(0.601)	-0.165	(0.688)
Diversity among foreigners	0.217	(0.141)	0.197	(0.162)	0.294	(0.313)	-0.109	(0.249)
Regional specific variables (excluding the plant's own contribution)								
Share of foreigners	1.813	(3.627)	-0.403	(3.829)	11.419*	(4.854)	-6.353	(5.924)
Diversity among foreigners	1.580**	(0.789)	-0.091	(0.857)	2.052**	(0.854)	-1.995*	(1.147)
Statistics								
Number of observations	5,794		1,447		3,043		1,059	
Number of instruments	570		570		563		530	
Hansen J p-value	0.521		1.000		0.835		1.000	
AR(1) p-value	0.000		0.000		0.000		0.000	
AR(2) p-value	0.216		0.101		0.689		0.177	

All comments and control variables as in table 5.4.

Table 5.7
System GMM estimates of the augmented production function –
Large and small plants.

	Manufacturing				Service			
	Large plants		Small plants		Large plants		Small plants	
Plant specific variables								
Share of foreigners	-1.220	(0.923)	-0.073	(0.833)	0.655	(0.632)	-0.843*	(0.474)
Diversity among foreigners	0.286**	(0.137)	0.364	(0.546)	0.053	(0.285)	-0.015	(0.342)
Regional specific variables (excluding the plant's own contribution)								
Share of foreigners	3.986	(3.673)	-8.132	(28.486)	3.877	(9.071)	6.778	(4.592)
Diversity among foreigners	1.004	(0.782)	0.897	(1.905)	-0.943	(2.257)	2.340***	(0.756)
Statistics								
Number of observations	4,322		2,918		1,768		2,334	
Number of instruments	580		549		573		553	
Hansen J p-value	0.933		0.950		1.000		0.990	
AR(1) p-value	0.000		0.000		0.000		0.000	
AR(2) p-value	0.256		0.270		0.337		0.414	

All comments and control variables as in table 5.4.

Table 5.8
System GMM estimates of the augmented production function – Exporters and foreign-owned plants.

	Exporter		Non-exporter		Foreign-owned plants		Domestic plants	
Plant specific variables								
Share of foreigners	0.696**	(0.349)	-0.662**	(0.274)	-0.976	(0.824)	-0.415	(0.317)
Diversity among foreigners	-0.144	(0.167)	0.040	(0.253)	0.197	(0.159)	0.195	(0.186)
Regional specific variables (excluding the plant's own contribution)								
Share of foreigners	-2.014	(3.411)	3.117	(4.370)	-7.865	(4.893)	0.583	(3.389)
Diversity among foreigners	1.551	(0.950)	1.429*	(0.750)	2.021**	(0.978)	1.532**	(0.723)
Statistics								
Number of observations	4,654		6,689		822		10,521	
Number of instruments	592		593		568		593	
Hansen J p-value	0.521		0.576		1.000		0.560	
AR(1) p-value	0.000		0.000		0.001		0.000	
AR(2) p-value	0.232		0.550		0.445		0.478	

All comments and control variables as in table 5.4.

Table 5.9
System GMM estimates of the augmented production function – Region types.

	Agglomerations		Other regions		Large regions (Size above median)		Small regions (Size below median)	
Plant specific variables								
Share of foreigners	0.524	(0.430)	-0.239	(0.550)	0.333	(0.423)	-0.515	(0.689)
Diversity among foreigners	0.172	(0.205)	0.036	(0.207)	0.134	(0.156)	0.087	(0.231)
Regional specific variables (excluding the plant's own contribution)								
Share of foreigners	-4.353	(4.553)	2.113	(5.156)	-4.516	(3.573)	-1.723	(5.461)
Diversity among foreigners	0.449	(1.477)	1.401**	(0.601)	0.580	(1.305)	1.155**	(0.586)
Statistics								
Number of observations	3,930		7,413		5,672		5,671	
Number of instruments	578		586		590		589	
Hansen J p-value	1.000		0.564		0.715		0.467	
AR(1) p-value	0.000		0.000		0.000		0.000	
AR(2) p-value	0.125		0.738		0.223		0.535	

All comments and control variables as in table 5.4.

Table 5.10
System GMM estimates of the augmented production function –
Additional regional control variables.

	Manufacturing		Services	
Plant specific variables				
Share of foreigners	-0.012	(0.317)	-0.962*	(0.571)
Diversity among foreigners	0.270**	(0.136)	0.016	(0.270)
Regional specific variables (excluding the plant's own contribution)				
Share of foreigners	-0.915	(2.724)	3.153	(5.002)
Diversity among foreigners	1.730***	(0.647)	1.765**	(0.708)
Statistics				
Number of observations	7,241		4,102	
Number of instruments	581		574	
Hansen J p-value	0.435		0.424	
AR(1) p-value	0.000		0.000	
AR(2) p-value	0.128		0.751	

All comments and control variables as in table 5.4.

Table 5.11
System GMM estimates of the augmented production function –
Excluding the plants' own industry.

	Manufacturing		Services	
Plant specific variables				
Share of foreigners	-0.047	(0.369)	-0.821	(0.569)
Diversity among foreigners	0.304**	(0.142)	0.013	(0.277)
Regional specific variables (excluding the industry's own contribution)				
Share of foreigners	0.265	(3.115)	3.648	(4.800)
Diversity among foreigners	1.268*	(0.671)	1.588*	(0.821)
Statistics				
Number of observations	7,241		4,102	
Number of instruments	580		573	
Hansen J p-value	0.528		0.389	
AR(1) p-value	0.000		0.000	
AR(2) p-value	0.118		0.773	

All comments and control variables as in table 5.4.

Table 5.12

System GMM estimates of the augmented production function –
Diversity within skill groups.

	Manufacturing		Services	
Plant specific variables				
Share of high skilled foreigners	-0.424	(0.332)	0.110	(0.317)
Share of less skilled foreigners	-0.197	(0.291)	0.432	(0.282)
Diversity among high skilled foreigners	0.121	(0.135)	-0.272	(0.280)
Diversity among less skilled foreigners	0.182	(0.144)	-0.353	(0.230)
Regional specific variables (excluding the plant's own contribution)				
Share of high skilled foreigners	1.488	(5.765)	-11.812	(8.205)
Share of less skilled foreigners	-0.403	(1.912)	-0.265	(2.295)
Diversity among high skilled foreigners	0.356	(0.255)	0.228	(0.379)
Diversity among less skilled foreigners	0.311	(0.516)	0.593	(0.788)
Statistics				
Number of observations	7,241		4,102	
Number of instruments	832		822	
Hansen J p-value	0.742		0.999	
AR(1) p-value	0.000		0.000	
AR(2) p-value	0.112		0.769	

All comments and control variables as in table 5.4.

Table 5.13
System GMM estimates of the augmented production function –
Controlling for the occupational mix.

	Manufacturing		Services	
Plant specific variables				
Share of foreigners	0.008	(0.374)	-0.880	(0.571)
Diversity among foreigners	0.294**	(0.136)	0.050	(0.272)
Regional specific variables (excluding the plant's own contribution)				
Share of foreigners	0.686	(3.153)	3.411	(4.615)
Diversity among foreigners	1.599**	(0.781)	1.525*	(0.802)
Statistics				
Number of observations	7,241		4,102	
Number of instruments	565		558	
Hansen J p-value	0.512		0.411	
AR(1) p-value	0.000		0.000	
AR(2) p-value	0.167		0.993	

All comments and control variables as in table 5.4.

Table 5.14
System GMM estimates of the augmented production function –
Sales as dependent variable.

	Manufacturing		Services	
Plant specific variables				
Share of foreigners	-0.120	(0.341)	-0.063	(0.195)
Diversity among foreigners	0.029	(0.094)	0.091	(0.072)
Regional specific variables (excluding the plant's own contribution)				
Share of foreigners	0.324	(1.829)	0.403	(1.452)
Diversity among foreigners	0.802**	(0.406)	0.550**	(0.275)
Statistics				
Number of observations	11,343		11,343	
Number of instruments	594		657	
Hansen J p-value	0.134		0.160	
AR(1) p-value	0.000		0.000	
AR(2) p-value	0.979		0.464	

All comments and control variables as in table 5.4.

Table 5.15
System GMM estimates of the augmented production function –
University degree as skill measure.

	Diversity among all foreigners		Diversity by skill group		
Plant specific variables					
Share of foreigners	-0.552	(0.627)	0.297	(0.252)	Share of high skilled foreigners
			0.069	(0.293)	Share of less skilled foreigners
Diversity among foreigners	0.063	(0.158)	0.014	(0.145)	Diversity among high skilled foreigners
			-0.205	(0.145)	Diversity among less skilled foreigners
Regional specific variables (excluding the plant's own contribution)					
Share of foreigners	2.256	(3.270)	2.756	(3.078)	Share of high skilled foreigners
			-2.496	(2.711)	Share of less skilled foreigners
Diversity among foreigners	0.757	(0.738)	0.187	(0.330)	Diversity among high skilled foreigners
			0.026	(0.643)	Diversity among less skilled foreigners
Statistics					
Number of observations	6,543			6,543	Number of observations
Number of instruments	594			846	Number of instruments
Hansen J p-value	0.498			0.428	Hansen J p-value
AR(1) p-value	0.000			0.000	AR(1) p-value
AR(2) p-value	0.115			0.098	AR(2) p-value

All comments and control variables as in table 5.4.

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Erklärung

**gemäß §10 Abs. 6 der Promotionsordnung der Mercator School of Management,
Fakultät für Betriebswirtschaftslehre der Universität Duisburg-Essen vom 11. Juni 2012.**

“Hiermit versichere ich, dass ich die vorliegende Dissertation selbstständig und ohne unerlaubte Hilfe angefertigt und andere als die in der Dissertation angegebene Hilfsmittel benutzt habe. Alle Stellen, die wörtlich oder sinngemäß aus anderen Schriften entnommen sind, habe ich als solche kenntlich gemacht.”

Michaela Trax